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ASSESSING THE QUALITY OF THE BALTIC EQUITY MARKETS: MICRO-LEVEL APPROACH

Authors: Žybartas Gineitis
Ieva Pajarskaitė

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Žybartas Gineitis

and

Ieva Pajarskaitė

Supervisor: Tālis Putniņš

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Abstract

In this research we compute a summary measure of market quality for a sample of stocks in the Baltic equity markets. The measure is based on Beveridge-Nelson decomposition of transaction price series into random walk (consensus efficient price) and stationary (pricing error) components. Using a unique dataset with investor level data from Tallinn stock exchange we further investigate the role of different agents in the context of market quality. The analysis of trade level data reveals that institutions improve the quality of the market by informed trading and market making, latter being the stronger determinant. Also, although economically insignificant, results provide evidence that traders' experience is associated with higher market quality.

Keywords: Baltic stock markets, Beveridge-Nelson decomposition, efficient price, institutional trading, Lee-Ready algorithm, market making, market quality, micro-level, pricing error, random walk, traders' experience.

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1. Introduction

Equity markets exist in order to allow the efficient allocation of financial capital among alternative investment opportunities. The efficient allocation relies on informative prices, which act as signals to agents responsible for real investments. Prices change as a consequence of market participants acquiring information, revaluing securities and trading according to these subjective evaluations. Since prices are formed inside the structure of markets that constrain the aptitude of individuals to trade, it necessarily follows that transaction prices are subject to the same constraints. Consequently, efficient allocation of capital relies on the market structure as well. An admirable market structure would be the one under which prices follow consensus valuation of the public. In other words, the extent to which transaction prices are independent from market imperfections define market quality.

The research on market quality is usually based on various related concepts like liquidity, tightness of the bid-ask spread or informational efficiency. However, to understand the net effect of various quality determinants a summary measure of market quality would be valuable; unfortunately, it is rarely used since not many alternatives for such a measure exist. Moreover, cross-sectional and longitudinal differences in market quality are usually explained by firm specific factors, while trader level determinants are overlooked. In addition, many studies use daily or monthly data which does not allow capturing micro-level structural inefficiencies. This in large part can be attributed to low availability of high-frequency investor level data.

This research investigates the quality of the Baltic equity markets in Vilnius, Riga and Tallinn. The Baltic equity markets are commonly known as being underdeveloped as compared to such markets like NYSE, AMEX or NASDAQ. Although the Baltic equity markets have been operating for nearly two decades, such phenomena like thin trading and low liquidity have been present throughout the whole history of these young markets. It seems that they never took off in terms of quality.

The first part of the research is devoted to the search and development of the summary market quality measure for the Baltic equity markets. The second part aims at evaluating the role of different agents in the context of market quality and answering two research questions: (1) How institutional trading affects market quality? (2) How trader's experience affects market quality?

In order to answer the research questions authors test and apply a summary measure of market quality based on transaction price series decomposition into permanent and transitory components interpreted as the consensus efficient price and the pricing error respectively. Authors not only evaluate the applicability and possible limitations of the original methodology proposed by Hasbrouck (1993) to the Baltic equity markets but also suggest methodology improvement which enhances accuracy of the estimates and make the methodology more suitable for illiquid emerging markets. On top of that, authors examine the overall impact and mechanisms that link institutional trading with market quality. Finally, the relation between trader's experience and market quality is evaluated for both individual and institutional traders.

The findings suggest that institutional trading has a significant and economically meaningful positive effect on market quality. In addition, quality enhancement from liquidity providing turns out to be more important than the active correction of identified stock mispricing. The effect of experience on market quality seems to be positive but economically insignificant.

The research has five key contributions. First of all, it develops the methodology for summary market quality estimation which is more accurate and more suitable for illiquid markets than the initial model. Secondly, this study contributes to the present empirical research by evaluating the role of different agents in the context of market quality. This line of research gives a valuable insight on alternative (not firm specific) determinants of market quality. Thirdly, the study evaluates the development of the Baltic equity markets using micro level approach which allows capturing short-term market imperfections not visible in longer horizons. Fourthly, the findings have practical implications on market design – knowing agent specific determinants of market quality, the market design can be altered to accommodate the factors that improve market quality the most. The fifth contribution is that besides answering the research questions authors provide the evaluation of the most popular trade classification algorithms into buyer and seller initiated trades. This is highly relevant for any researcher that needs to perform trade classification in the context of the Baltic equity markets or any other emerging market having similar market features.

The rest of this paper is organized as follows. Section II provides literature review about alternative market quality measures, the development of the summary market quality measure, existing literature assessing the quality of the Baltic equity markets as well as the effects of institutional trading and investors' experience on market quality. Section III describes the methodology; Section IV describes data used in the research and provides evaluation of the trades' classification algorithms. Section V presents results and their discussion, and section VI concludes.

2. Literature Review

Various aspects of market quality have been one of the most commonly discussed topics concerning equity markets in general, and market microstructure in particular. However, the term "market quality" is a very broad concept. It captures a number of market features such as market liquidity, implicit and explicit trading costs, informational efficiency, volatility and etc. The importance and applicability of one summary market quality measure is obvious: it serves in analyzing market performance (Hasbrouck, 1993), comparing various stock exchange systems (e.g. Krishnamurti, Sequeira & Fu, 2003), evaluating regulatory impact (e.g. Albanesi & Rindi, 2000) or estimating explicit or implicit trading costs faced by investors (e.g. Berkowitz, Logue & Noser, 1988; Breen, Hodrick & Korajczyk, 2002). Unfortunately, due to conceptual complexity it is difficult to derive one summary measure which would reflect multiple aspects of market quality. Previous studies that investigated market quality employed a number of different measures; however, majority of them suffer from limitations that do not allow interpreting them as valid summary market quality measures. We present the most popular practices to evaluate market quality as well as discuss the limitations of these estimates.

2.1. Alternative Market Quality Measures

One line of studies concentrates on market liquidity as a measure of market quality. Liquidity of the market is commonly described by certain features such as market tightness, depth, immediacy and resilience. Traditionally, market depth was the most commonly discussed in academic research. The most straightforward measure would be the quoted market depth defined as a number of securities that are explicitly listed for selling or buying at the posted quotes. However, this measure tends to underestimate the true market depth as full quantities that market participants are willing to transact are not always revealed (Fleming, 2003). Therefore, various measures relating price changes to trading volumes were employed to estimate the effective market depth. A classical paper in the field of price impact studies was presented by Kyle (1985) where a measure of liquidity sometimes referred as Kyle's lambda or Kyle's measure of market depth was introduced. This popular measure relates price changes with an order flow and is typically estimated by regressing price changes on net volume for fixed time intervals. Other studies estimating the price impact include Glosten and Harris (1988), Hasbrouck (1988, 1991) and Breen, Hodrick and

Korajczyk (2002). Engle and Lange (2001) propose a slight modification of the measure: effective market depth is defined as the number of shares that can be bought or sold within a given price range.

Despite high popularity and relevance price impact approach has certain limitations that do not allow interpreting this measure as a valid estimate for market quality. The most important problem is pointed out by Grossman and Miller (1988). The price impact measure fails to distinguish among the sources of price volatility and cannot differentiate between the transient price impacts which occur due to low market quality and the persistent impacts that reflect new information incorporation into the efficient price. Therefore, price variability may occur not due to illiquidity but due to frequently arriving fundamental information.

Another approach to evaluate market quality is by measuring trading costs. The intuition behind is that higher quality of market microstructure should be reflected in lower transaction costs. Even though some costs such as commission fees are explicitly stated, what really matters for investors are the implicit trading costs. Unfortunately, implicit costs are directly unobservable and hard to estimate. There are numerous methods employed in existing literature trying to obtain an estimate for the implicit trading costs.

One of the most straightforward measures commonly applied in various studies to capture trading costs is the bid-ask spread. Starting from the pioneering studies in the 70's (e.g. Damsetz, 1968) the quoted bid-ask spread has been a commonly used measure of trading costs employed by both researchers and practitioners. Divergence between buying and selling prices used to be interpreted as a proxy for transaction costs and market efficiency (Branch and Freed, 1977; Benston and Hagerman, 1974; Huang and Stoll, 1996a,b; Barclay et al., 1999). The measure served in comparing trading costs between markets and over time (Grossman and Miller, 1988). The measure is very attractive because of its simplicity as it can be directly taken from publically available data.

However, there is a clear consensus in academic literature providing a strong critique of the bid-ask spread as a measure of market quality. Hasbrouck (1993) points out that the stated spread can be interpreted as twice the transaction cost for market-order trader only under numerous restrictive assumptions that are usually not realistic. Hasbrouck (1991) argues that the quoted spread has significant limitations as it is conditioned on trades of a certain size and is often valid only for small trading volumes. Engle and Lange (2001) point out the same problem of capturing the market tightness only for low-volume trades and failing to measure trading costs for large orders that, according to the authors, almost always face worse execution. In this way the measure does not provide full trading cost information that is highly relevant for impatient, high-volume traders. This limitation is especially relevant for the Baltic stock markets where a significant part of trades occur at prices outside the quoted spread. Ellis, Michaeley and O'Hara (2000) go even further by stating that trading at prices different from bid-ask quotes is increasingly common in all markets. A number of researchers find that the quoted spread is not capturing all the liquidity available in the market. For instance, Blume and Goldstein (1992) find that between 12% and 31% of the trades in cross-market sample occur inside the spread. Lee (1993) reports a 30-40% rate depending on the stock exchange, Ellis, Michaeley & O'Hara (2000) find a 25% rate. The phenomenon of the effective spread being narrower than the quoted spread is specific to more developed markets and it is not directly relevant for the Baltic stock markets where dealers that could provide quote improvement are not existent. To sum up, large proportion of trades occurring at prices different from the quotes (usually outside the spread in the Baltics) make quoted bid-ask spread a noisy measure of transaction costs or market liquidity (Brennan and Subrahmanyam, 1996) and it cannot be interpreted as a reasonable summary market quality measure.

Some problems with bid-ask spread measure can be mitigated by calculating effective bid-ask spread. This approach has been used by e.g. Barclay (1997, 1999); Bessembinder (1997); Christie and Huang (1994); Christie and Schultz (1994); Huang and Stoll (1996). However, even in this case the bid-ask spread lacks a sound interpretation as a good summary market quality measure.

Some researchers decided to use the variance ratio. The underlying idea is that market imperfections and execution costs have transitory effect on the stock price and increase short-term volatility relative to the long-run volatility of price movements. The extent to which the variance ratio (long-term volatility divided by short-term volatility) deviates from one is interpreted as a measure of market performance. This methodology has been implemented by Barnea (1974) and Hasbrouck and Schwartz (1988). However, in his later work Hasbrouck (1993) provides a strong critique of the measure as it suffers from high sensitivity to the horizons used and lacks general connection to conventional transaction cost measures.

An alternative method to obtain an estimate for the market quality is calculating the difference between the actual transaction price and the efficient price. The intuition behind this approach is very appealing: all market imperfections should be reflected in the divergence from the "equilibrium" or "fair" price. The deviations are supposed to capture various aspects such as direct transaction costs, e.g. commission fees, and implicit market impact costs related to market illiquidity, pricing inefficiency and etc. However, the problem with this methodological approach is the estimation of this “fair” value as it is an unobservable measure. Early attempts to estimate a proxy for the efficient price (Beebower, 1989; Berkowitz, Logue and Noser, 1988) based on high–low midpoint prices, closing prices or volume weighted daily averages suffers from severe problems due to biased representation and no clear theoretical reasoning why they should be interpreted as an efficient price.

The pivotal paper in this field of research was presented by Hasbrouck (1993). He presented a proxy for the efficient price based on Beveridge-Nelson (1981) time series decomposition into the permanent and transitory components. Random walk component is interpreted as an efficient price as it reflects price movements that occur due to information that is permanently impounded in the stock price; the transitory component is supposed to capture temporary pricing errors caused by the imperfections of the market micro-structure. We perceive this measure as one of the most appropriate summary measures of market quality developed so far in a sense that it captures and summarizes all previously mentioned aspects of market quality such as liquidity (price impact), transaction costs (bid-ask spread), informational efficiency (permanent price impact versus short run fluctuations) and many others that do not have to be modeled explicitly. The development of the model as well as the detailed interpretation of the summary market quality measure is provided in the following sections.

2.2. Modeling economic time series

Econometric methods used to decompose time series into transitory and permanent components were first developed to analyze GDP data and business cycle of an economy. The general idea was that economic data consists of the long run (trend) component and the temporary (cycle) component (Watson, 1986; Nelson, 2008). Proper estimation of these components in macroeconomic data was important for the estimation of relationships between variables and thus empirical testing of theories (Watson, 1986). This is also the case in microstructure research in financial markets.

Most of economic series are non-stationary – trending over time. The simplest way to model such series would be assuming a deterministic trend with stationary cycle around it. However this would imply that economic series are predictable over long horizons, which is not the case (Watson, 1986). Beveridge and Nelson (1981) suggested defining trend as long run forecast of the series conditioned on all past data. At every point in time this trend will shift since every period new information is revealed in the series. It follows that the remainder component is temporary and can be attributed to business cycle. However, the method operates under the assumption that trend and cycle processes share the same innovation at every period, which might not be a reasonable assumption with economic series (Maravall, 1995). Morley (2009) using the Monte Carlo method concludes that this assumption does not compromise permanent and cycle component estimations; however, in macroeconomic series estimates of standard deviation of cycle component might be biased if assuming perfect correlation between innovations of the two processes leads to misspecification of the model.

Watson (1986) suggests another extreme case of such decomposition, where trend and cycle components have uncorrelated innovations. Both models with zero and perfect correlation between innovations are econometrically identifiable, however more general case – a mixture of both – is not.

2.3. Decomposition of security prices

Classical economic argument about security prices in the financial markets states that due to competitive trading and costless information, prices impound and reflect all available information at any given moment in time. This in turn implies that security prices are martingales. This should result in security prices having identical properties with a random walk. However, at micro-level, trading costs and other constraints play a significant role and therefore prices deviate from what we could consider a random walk (Hasbrouck, 2002). It follows that the security prices are composed of random walk and stationary components. The later is present due to market microstructure effects. Decomposing security prices into these two components is quite popular in empirical microstructure literature. (Hasbrouck, 1991, 1993, 2002; Huang & Stoll, 1997). Applications are tipically related to quality, informational efficiency and cointegration of the stock markets.

Like most of the economic series, security prices are usualy non-stationary and integrated of first order. Box and Jenkins (1968) show that these kind of processes can be modeled as ARIMA (p,1,q) processes: autoregressive (AR) integrated (I(1)) moving average (MA). There are several decompositions of these components, but Beveridge-Nelson (1981) decomposition, as shown by Watson (1986), provides the best linear estimates of the two components. Hasbrouck (1993) was one of the first attempts to apply the decomposition to intraday security price series as well as identify permanent and transitory components as the "efficient price" and "pricing error". This particular decomposition is widely used in microstructure setting (Hasbrouck, 1993; Hotchkiss & Ronen, 2002; Boehmer, Saar, & Lei, 2005; Boehmer & Kelley, 2007).

2.4. Standard deviation of pricing error

In the model proposed by Hasbrouck (1993) the estimation of the market quality measure is based on the evaluation of the short-run informational efficiency of the market. Given the theoretically established proposition that the efficient price should be reflected by the random walk component of the time series, the cyclical component calculated as the difference between the actual transaction and the estimated efficient price can be interpreted as a transient disturbance caused by imperfections of the trading mechanism (Hasbrouck, 2002). As the expected value of the pricing error by construction is zero, the dispersion of the stationary component which reflects how closely actual transaction price tracks a random walk naturally becomes a measure of market quality (Hasbrouck, 1993). As market microstructure effects are likely to have only transitory and no permanent effect on the stock price it is reasonable to believe that the pricing error component captures implicit trading costs that occur due to imperfection of the market (Hasbrouck, 2002).

Variance of the pricing error should be interpreted as a summary measure of market quality as it captures market microstructure imperfection effects in aggregate without explicit modeling of single effects. Variation of the pricing error does not have a direct transaction-cost interpretation. However, it can be used as a valid market quality measure in a sense that lower transaction costs and other barriers for trading should move actual transaction prices closer to the efficient ones. Hasbrouck (1993; 2002) and Boehmer and Kelley (2007) list a number of imperfections that can be captured by the pricing error: bid – ask bounce, price discreteness, inventory effects, order imbalances, transient liquidity effects, "noise" trading, adverse-selection effects, lagged adjustment to information and etc.

Note that due to the focus on the short-run effects the model does not consider whether the actual prices are efficient in the absolute sense, i.e. whether they efficiently reflect fundamental information and provide the most efficient capital allocation in the society (Boehmer & Kelley, 2007). Any daily or longer term deviations from the random walk, the phenomenon that has been found by e.g. Lo and MacKinlay (1988), Fama and French (1988), Poterba and Summers (1988) are not captured by the model as it allows only short-run (several transaction) serial dependencies. The market microstructure imperfections are expected to have only short-run transitory effect on stock prices and are captured by the measure of pricing error volatility. In contrast, longer term deviations from the random walk, that are not a subject of interest for this research, are assigned to the permanent component part of the decomposition (Hasbrouck, 1993). Therefore, it is important to understand that the model measures deviations from the prevailing consensus price rather than company's fundamentals.

The variance of the pricing error exhibits some features that are superior to the other market quality measures discussed in the previous section. First of all, this estimate captures multiple market microstructure effects; therefore, it has a sound interpretation as a summary market quality measure. Secondly, it is superior to other measures by its ability to distinguish between permanent price changes due to incorporation of new information and transitory price impact due to market frictions. Finally, it uses trading time instead of clock time which helps capturing smaller market imperfection which would be overlooked by other market quality measures (Boehmer & Kelley, 2007).

2.5. Quality of the Baltic stock markets

Concerning the quality of the Baltic equity markets, Čekauskas, Gerasimovs, Liatukas and Putniņš (2011) provide time series and cross-sectional description of the three Baltic equity markets. In total six market quality measures are employed: three of them measure the liquidity of the market while other three are constructed to reflect informational efficiency. The study finds empirical evidence that Tallinn and Vilnius markets outperform Riga in terms of market quality. Concerning the longitudinal differences no significant improvement over time is reported. The liquidity turned out to be highly affected by the market crunch in 2008-2010 while informational efficiency remained quite stable over time.

2.6. Institutional trading and market quality

Even though a number of studies investigated the role of institutional investors in the equity markets only a few of them provide direct evidence how institutional activities affect market quality and informational efficiency. Sias, Starks, and Titman (2006) show that institutional trading lead to faster information incorporation; Bartov, Radhakrishnan and Krinsky (2000) prove that greater institutional ownership is associated with lower post-earnings announcement drift. Boehmer and Kelley (2007) go further and investigate the channels how institutional ownership affects market quality. They suggest that one of the most important channels is institutional trading and distinguish between active and passive institutional trading. Firstly, by actively trading on private information institutions could improve informational efficiency by identifying and correcting stocks' mispricing. In this case institutions demand quick order execution and become active traders that consumes liquidity. Secondly, institutional traders are expected to have better abilities than other traders to distinguish between informed and uninformed trading. Therefore, they benefit from passively providing liquidity for larger uninformed orders whose buying or selling pressure would otherwise cause prices to deviate from their consensus value. Boehmer and Kelley (2007) find evidence that both active and passive institutional trading leads to better informational efficiency. Also they report that passive institutional trading tends to have a more significant impact on market quality than active trading.

2.7. Experience and market quality

In economics and finance literature the mechanisms of human learning and its effects on market efficiency or quality are not clearly defined. Despite the underlying constructs, empirical literature seems to agree upon the significance of traders' experience and market quality. Most evidence on this relationship comes from laboratory markets, where efficient price is known and experimental setting gives sufficient control to conclusively demonstrate learning effects on pricing error. Ketcham, Smith and Williams (1984) made a comparison of posted-offer and double-auction laboratory markets. The benchmark was competitive equilibrium and results showed that more experienced traders had lower root mean square error in prices as well as lower absolute mean error and positively influenced efficiency. In research by Cason and Friedman (1997) subjects were trading in an artificial single call market. The subjects with previous experience in single call markets (in laboratory setting) were systematically outperforming subjects who were familiarized with the setting, but did not have previous experience. Prices in markets with more experienced traders were closer to the efficient price. Other research manipulates common knowledge, aggregate uncertainty (Forsythe & Lundholm,1990) and market size (Lundholm, 1991) and find positive effects of experience on market efficiency as well. Oliven and Rietz (2004) carried out a research in Iowa Electronic Markets - experimental futures markets that are complete in a sense that all states have a portfolio that yields a payoff of 1 dollar in that particular state and zero otherwise as well as that a risk-free portfolio exists. Analysis looked for determinants of trading mistakes that resulted in either arbitrage opportunities or did not minimize trading costs for the individual. Investor and trade level data showed that financial knowledge and amount of trades performed are important factors in explaining the likelihood of trading mistakes at individual level.

3. Methodology

3.1. First stage

In this section we provide a detailed description of the methods used in our analysis. First, the theoretical framework that will be used to model transaction prices is presented, and then econometric identification is derived.

To mitigate problems of normality and interpretability we use natural logarithm of stock prices. First, we take the transaction price in time t as made up of two components:

$$p_t = m_t + s_t. \quad (1)$$

At any given moment in time t transaction price consists of efficient price (m_t) and pricing error (s_t) components. Efficient price is defined as long horizon expectation of value of the security that impounds all public information. Deviation of the transaction price from the efficient price (s_t) is called the pricing error. It must be noted that t can denote either clock time or transaction time. In the present work transaction time is used.

To apply Beveridge-Nelson decomposition we have to assume the following properties of these two components:

$$m_t = m_{t-1} + \omega_t. \quad (2)$$

The efficient price follows a random walk, where ω_t zero-mean, serially uncorrelated innovations to the efficient price. These innovations are the new information impounded into efficient price every period. Second assumption is that pricing error is a zero-mean covariance-stationary process, in other words, pricing error is wide-sense stationary.

Further, the pricing error component can be decomposed into information correlated ($\alpha\omega_t$) and information uncorrelated (η_t) components.

$$s_t = \alpha\omega_t + \eta_t. \quad (3)$$

Using Beveridge-Nelson decomposition we must impose a restriction that innovations in the efficient price and the pricing error are perfectly correlated, namely: $\alpha \neq 0, \eta_t = 0$, thus pricing error takes the following form:

$$s_t = \alpha\omega_t. \quad (4)$$

Due to this restriction estimate of variance of the pricing error contains only the lower bound of the true variance (Hasbrouck, 1993).

From equation (1),(2) and (4) the return is:

$$r_t = p_t - p_{t-1} = m_t - m_{t-1} + s_t - s_{t-1} = (1+\alpha)\omega_t - \alpha\omega_{t-1}. \quad (5)$$

In current case, returns take a form of first order moving average:

$$r_t = \epsilon_t - a\epsilon_{t-1} \quad (6)$$

It follows that $(1+\alpha)\omega_t - \alpha\omega_{t-1} = \epsilon_t - a\epsilon_{t-1}, \alpha = \frac{a}{1-a}, \omega_t = (1-a)\epsilon_t, s_t = \alpha\omega_t, \sigma_\omega^2 = (1-a)^2\sigma_\epsilon^2, \sigma_s^2 = a^2\sigma_\epsilon^2$.

Using substitution and recursion from equation (6) we can estimate pricing error as:

$$\hat{s}_t(r_t, r_{t-1}, r_{t-2}, \dots) = -a\epsilon_t = -a(r_t + ar_{t-1} + a^2 r_{t-2} + \cdots). \quad (7)$$

Under Beveridge-Nelson restriction, this estimate is exact (Watson, 1986; Morley, 2009). However, the estimate of variance is only the lower bound. Hasbrouck (1993) argues that the estimate can be strenthened by adding more explanatory variables. This can be done by further decomposing innovation component in (2):

$$\omega_t = \gamma x_t + u_t, \tag{8}$$

where x_t is trade volume that takes possitive sign, when transaction is initiated by the buyer and negative sign in case of seller initiated transaction. The first component (γx_t) denotes private information that becomes public due to the trade and second component (u_t) denotes new public information at time t.

$$s_t = \alpha x_t + \beta u_t \tag{9}$$

From (8) and (9) returns can be expressed as:

$$r_t = (\gamma + \alpha)x_t - \alpha x_{t-1} + (1 + \beta)u_t - \beta u_{t-1}. \tag{10}$$

From this expression it is obvious that we can represent returns as a regression with a moving average error term:

$$r_t = b_0 x_t + b_1 x_{t-1} + \epsilon_t - a\epsilon_{t-1}. \tag{11}$$

In this case the variance of standard error is calculated as $\sigma_s^2 = \alpha^2\sigma_x^2 + \beta^2\sigma_u^2$,

$$\alpha = -b_1, \gamma = b_0 + b_1, \beta = \frac{a}{1-a}, u_t = (1+a)\epsilon_t, \sigma_u^2 = (1-a)^2\sigma_\epsilon^2,$$

$\sigma_s^2 = \alpha^2\sigma_x^2 + a^2\sigma_\epsilon^2$.

To generalize the model to any number of explanatory variables and allow for serial correlations in returns VAR model is used:

$$\begin{aligned} r_t &= a_1 r_{t-1} + a_2 r_{t-2} + \cdots + b_1 x_{t-1} + b_2 x_{t-2} + \cdots + v_{1,t}, \\ x_t &= c_1 r_{t-1} + c_2 r_{t-2} + \cdots + d_1 x_{t-1} + d_2 x_{t-2} + \cdots + v_{2,t}. \end{aligned} \tag{12}$$

In this case x_t is a vector of explanatory variables, therefore elements on the right hand side of the lower equation denote vectors and matrixes.

We further augment the original methodology first suggested by Hasbrouck (1993) which could be found in appendix IV by using an alternative method to compute Beveridge–Nelson decomposition suggested by Arino and Newbold (1998). The method provides direct Beveridge–Nelson decomposition formula for VARMA processes, thus eliminating the need to convert it into VMA (which in turn requires truncation). Traditional expresion is redirived (in case of VAR) into:

$$\hat{s}_t = \lim_{k\to\infty} \sum_{j=1}^{k} \begin{bmatrix} r_{t+j} \\ x_{t+j} \end{bmatrix} = [A(1)]^{-1} \sum_{j=1}^{p} \sum_{i=j}^{p} A_i \begin{bmatrix} r_{t+1-j} \\ x_{t+1-j} \end{bmatrix}, \tag{13}$$

where $A(\cdot) = I - A_1 \cdot - A_2 \cdot^2 - \cdots - A_p \cdot^p$ and $A_i = \begin{bmatrix} a_i & b_i \\ c_i & d_i \end{bmatrix}$. It must be noted that in this case $\hat{s}_t$ is a column vector and the first element is the one of interest to this research. To compute the covariance matrix we first express pricing error as follows:

$$\hat{s}_t = B \begin{bmatrix} r_t \\ x_t \end{bmatrix}, \tag{14}$$

where $B = [A(1)]^{-1} \sum_j^p \sum_{i=j}^p A_j L^{j-1}$. Computation of covariance matrix is straight forward:

$$E[{s_t}^2] = E\left[B \begin{bmatrix} r_t \\ x_t \end{bmatrix} [r_t \quad x_t] B'\right]. \tag{15}$$

The first component of this matrix is the lower bound of the variance of the pricing error.

The alternative lower bound of the dispersion of the pricing error computation method developed in this thesis and based on the formula derived by Arino and Newbold (1998) has a twofold advantage over the original computation method applied by Hasbrouck (1993). First of all, it is superior from the theoretical point of view as it makes the estimates more accurate by avoiding the truncation of lags which would be necessary to convert VAR process into VMA. Secondly, a newly developed computation method is much more suitable for illiquid emerging markets such as the Baltic equity markets which suffer from severe illiquidity and low trading activity. Inversion method applied by Hasbrouck (1993) estimates pricing error using present and lagged values of estimated residuals, which in turn are estimated using present and lagged values of returns and lagged values of explanatory variables. The alternative computation used in the present research uses returns directly, without estimating residuals or inverting VAR into VMA. Inversion process does not allow computation of the pricing error for a certain number (two times the number of lags minus one) of observations after each restart of the regression in this way shrinking the effective sample size used for the computation of the dispersion of the pricing error. In contrast to the inversion method the alternative method skips approximately half the number of observations (the number of lags minus one). For example, Hasbrouck (1993) method for a model with 5 lags would not be able to estimate the pricing error for the first 9 observations after a restart while the alternative method would skip only the first 4 values. This feature of the model is very valuable for inactive emerging markets as it allows obtaining estimates for the days with relatively lower trading frequencies and mitigates bias towards the high frequency trading days.

3.2. VAR specification

Since the Baltic markets are atypically illiquid, authors acknowledged that the exact specification of the model might differ from the ones used in more developed markets. Before running the specification proposed by Hasbrouck (1993) we ran 6 different test specifications that included 2 different lag lengths and 3 different sets of explanatory variables. VAR was run for every stock separately through all the available sample period. Stocks that had less than 1000 trades over the sample period were excluded leaving the authors with a sample of 92 stocks in total. In order to reflect only short-term serial intraday dependencies and to mitigate the problem of stock splits, dividends and other inter-day effects, VAR was restarted every morning, thus overnight returns are excluded. Since the return data suffered from outliers, we winsorized the returns at first and last percentiles. A similar procedure was not performed on the volume data, since we use both, square root compressed and nominal signed volumes in our final VAR specification.

Three sets of explanatory variables included lagged returns and lagged signed volumes {r , x }, lagged returns and lagged signed logarithm of volumes {r, lnx}, and lagged returns, lagged signed square root of volume and lagged signed volume {r, sqrtx, x}. The choice of specifications is motivated by several factors. First, as mentioned, since the markets themselves are very different from the more developed ones, the true specification is unknown. Therefore authors start with the simplest one and adjust further specifications according to the results. Since volume has a lot of outliers, it was transformed into a logarithm in a second specification. Finally, to allow for non-linear return-volume relationship signed square root of volume and signed volume were used in the third specification. This final specification most closely resembles the one suggested by Hasbrouck (1993).

Lag length could not be determined using traditional information criteria such as Akaike, Hannan-Quinn or Schwarz-Bayesian, since in most stocks weak, but statistically significant dependencies are present at very large lags (15 and more). This would annihilate the usable sample size to a handful of stocks and days. However, this is not unusual in the empirical literature and common practice is to refer to common practice. Usually VAR is truncated at around 3-5 lags (Hasbrouck, 1993; Albanesi & Rindi, 2000). Following this norm two lag lengths were chosen - 3 and 5. Coupled with 3 sets of explanatory variables this resulted in 6 different model specifications.

After the sample of 92 stocks showed that there is a reasonable consistency between different specifications for stocks with larger number of trades in the data, the final specification was run. It had three main differences from the previous six specifications. First, previous specifications made an assumption that VAR coefficients were time invariant. To mitigate this potential bias, we estimate VAR coefficients annually. This was not done with previous specifications, since some stocks had too few observations for the VAR coefficients to have reasonably low standard errors. Secondly, the VAR was run only for the selected stocks that had at least 50% of days with 6 or more trades. Out of that sub-sample, at least half of the stocks had more than 80% of days with at least 6 trades. Finally, trade sign variable was included into the explanatory variable set to further strengthen the lower bound of standard deviation of the pricing error, so the final specification was {r, sign(x), sqrt(x), x}.

3.3. Second stage

In order to evaluate how institutional trading and traders' experience affect market quality the regression analysis is used. As each trade has two counterparties every pricing error appears in the dataset twice. The dependent variable is a numeric value of the pricing error of every transaction. Institutional dummy takes unity value for each trade side attributed to institutional investor. Trade initiator data allows identifying active and passive side of trade. Four dummies are generated to reflect one of the following combinations: institution (active) – institution (passive); institution (active) – private investor (passive); private investor (active) – institution (passive); private investor (active) – private investor (passive). The last group of trades is the reference group in all of the regressions. Only trades where identity of both counterparties is known are used in the analysis, i.e. institution trades via nominee accounts are not included as we cannot identify if the ultimate trader is private or institutional.

Three proxies for trading experience are constructed. Firstly, experience is measured by a cumulative number of trades that a particular investor has performed in the Tallinn stock market. Secondly, experience is measured by a cumulative volume traded in the market. Third proxy is defined as the time that has passed from the portfolio registration date. All measures are transformed into logarithms for two reasons – it transforms the distributions of the variables closer to normal distribution and interpretations are easier, since specification is identical to traditional learning curve. Data for variable construction is only available from 2004; therefore, old traders' experience is likely to be understated and this effect weakens over time. However, 3 years of trading (period January 2004-March 2007 not included in this regression) is perceived as a substantial lag to mitigate this bias. Interaction variable between institution dummy and experience is included to capture differences between private and institutional learning.

In addition to previously mentioned variables of interest a number of control variables are used to mitigate various biases. Monthly dummies for a period April 2007 – November 2010 are included to control for monthly specific time effects and stock dummies are used to capture stock fixed effects.

The model controls for investor-level factors that might correlate with both experience and pricing error. The factors include a dummy that indicates whether the trader is a foreigner (dummy value = 1) or local. Investor's wealth is measured by the logarithm of the yearly average value of the total holdings in the Tallinn stock market. Finally, the logarithm of the yearly average trade size is included.

Trade-specific factor that may correlate with experience and affect market quality is time of the day and it is controlled by inclusion of "opening" dummy for the first half an hour of the trading day and "closing" dummy for the last half an hour of the trading day.

In total there are two sets of experience proxies tested on two samples – one sample includes both institutions and individuals and the other sample includes only individuals. Four regressions took the following form:

$$\ln(|pricing\ error|)_{\mathrm{it}} = \beta_0 + \sum \beta_a \ln(X_a)_{it} + \sum \beta_b CP\ dummy_{b,it} + \sum \beta_c D_{it}^{Inst.} * \ln(X_a)_{it} + \sum \beta_d CV_{d,it} + \sum \beta_e D_{it}^{Inst.} * CV_{d,it} + \mu_i + \mu_t + \varepsilon_{it} ,$$

where $\mathrm{X_a}$ is a set of proxies for experience, two sets are used {cumulative number of trades, days of experience} and {cumulative volume traded, days of experience}. $\mathrm{CP\ dummy_b}$ – counterparty dummy indicating whether active and passive sides of the trade are institutions or individuals { institution (active) – institution (passive), institution (active) – private investor (passive), private investor (active) – institution (passive)}. Regressions with only individuals do not have "institution (active) – institution (passive)" dummy. $\mathrm{CV_d}$ are control variables. For regressions on full sample the set {ln(wealth), ln(average trade), foreigner dummy, opening dummy, closing dummy} of control variables is used. For regressions on individuals a set {ln(wealth), ln(average trade), foreigner dummy, gender dummy, ln(age), opening dummy, closing dummy} is used. The symbols μ_i and μ_t denote stock and month dummies. Interaction terms are present for all the proxies of experience and for {ln(wealth), ln(average trade), foreigner dummy} of control variables.

4. Data

4.1. Data description

This section provides a brief description of the data used for this study. The data consists of three parts. Trade and bid-ask information covers all stocks listed in the three Baltic Stock Exchanges, namely Nasdaq OMX Vilnius, Riga and Tallinn for the period from January 2005 to December 2011. Trader characteristics' information is available for stocks listed in Tallinn stock exchange for a period January 2004 - October 2010.

The first dataset was obtained from Nasdaq OMX Stockholm and it contains high-frequency trade information about each trade that took place in the Baltic stock markets during the sample period. The dataset contains information on the traded stock, market and submarket, transaction time, price, traded quantity, volume and trade type. In addition, it contains a measure that distinguishes between continuous market, internalized trades and auctions, and in case of continuous market trades it allows identifying which side of the trade added and which removed liquidity from the market. In total the dataset contains 2,057,842 observations for 138 stocks. The stocks that were traded less than 1000 times are removed leaving the dataset with 2,044,415 trades for 92 stocks. Note that the data does not suffer from the hindsight bias as information about delisted companies is not excluded from the analysis.

The second dataset provided by Nasdaq OMX Riga contains high-frequency information about each update of the best quoted bid and ask price. The dataset includes stock name, quote update time and the best bid and ask price. The dataset consist of 6,685,522 observations. This dataset is merged to the first dataset in order to compare trade price with the prevailing bid-ask spread.

The third dataset which was used for the second stage analysis was provided by Tālis Putniņš, the dataset was obtained from Estonian Central Securities Depository. The dataset contains-micro level records about every transaction in the Tallinn stock exchange for the period 2004-2010 as well as each trader's characteristics and monthly portfolio holdings. The dataset provides information about the traded security, price and quantity, trade date, direction (buy or sell) and each trader's identity in a form of a portfolio number. Trader specific characteristics include investor type (individual, institution, fund or government), investor gender, date of birth and identify whether the investor is a foreigner or local. Finally, the dataset provides information about exact portfolio holdings of each investor at the beginning of every month. Similar data is not available for Lithuania and Latvia as only

Estonia has a unique regulation system where individual accounts are directly registered in the securities depository. This dataset is merged to the first stage dataset. As trade characteristics datasets contains only trade date the match had to be done on the basis of trade date, price and volume. 78% of trades were merged successfully.

Due to thin order books big volume trades are commonly crossed off the stock exchange and reported with a certain delay up to a few days. In our dataset non-automatic trades account for 1.21% of total trades. However, they tend to be large: average non-automatic trade is 126 times larger than the average automatic trade (234,549 Euro versus 1,862 Euro) which leads to manual trades accounting for 61% of the total turnover. As non-automatic trades are reported with a delay while our model is very sensitive to time discrepancies the further analysis is applied only for automatic trades.

In February, 2009 the trading hours were prolonged from 4 continuous trading hours per day (from 10:00 until 14:00) to 6 trading hours (from 10:00 until 16:00). This structural change is not expected to cause inconsistencies for our analysis as in our model the natural time is ignored and data is treated as an untimed sequence of observations where time subscript denotes transaction number rather than clock time. In addition, the VAR is restarted every morning meaning that lag length never exceeds daily trading hours.

4.2. Trade ordering

Before February 8, 2010 NASDAQ OMX Baltics was using Saxess trading system which did not record the milliseconds at which trades were occurring. After the date mentioned, the system was changed into INET trading system, which recorded time of trades in milliseconds. Due to lower precision in time recording for older trades, a lot of trades in the dataset had the same time stamp. We used three methods to deal with this drawback. First, the trade groups that had identical time stamps and identical prices were collapsed into single trades which had a net volume of the group, meaning that the signed volume of the new trade was equal to the sum of signed volumes of the group. The groups that had identical time stamps, identical trade initiators (all buyers or all sellers), but different prices were sorted ascending if trade initiators were buyers and descending otherwise. The trade groups that had identical time stamps, but other characteristics were different were randomized. The last groups mentioned maid up less than 10% of the remaining dataset after the first mentioned groups of trades were collapsed, therefore this should not result in a significant bias.

4.3. Trade classification

The analysis requires trade classification into buyer- and seller-initiated trades. The authors of this paper have a unique opportunity to use a dataset with actual trade initiator information. This type of information for the Baltic countries has never been used in any research before and the accuracy of trade classification algorithms for the Baltic as well as majority of other emerging markets is unknown. Therefore, we not only use trade initiator information directly in our model, but also provide evaluation of the most popular algorithms and their applicability to the Baltic stock markets.

The information on the trade initiator is available starting from April 2007. For older periods this data has not been stored and recorded in Nasdaq OMX databases. Each transaction in the dataset has two legs: bid and ask. In addition, the dataset provides information which order added liquidity to the market and which removed liquidity. All trade legs that added liquidity are passive orders and all legs that removed liquidity are active orders. This information allows identifying whether the trade was buyer or seller initiated (e.g. buy order (bid) which removed liquidity from the market is classified as a buyer initiated trade and etc.). However, the trade initiator cannot be identified for three groups of trades that account for 26% of the sample: trades executed in one of the auctions, internalized during one of the auctions and internalized during the continuous market (Table 1).

Order Type	Percent
Added liquidity	35.8
Removed liquidity	37.9
Executed in one of the auctions	7.5
Internalized during one of the auctions	1.6
Internalized during the continuous market	17.2

Table 1. Source: authors’ calculations, using data from NASDAQ OMX Group (2012).

4.4. Trade classification algorithms

This section reviews trade classification algorithms used in the academic literature and evaluates their accuracy and applicability for the Baltic stock markets. There are 3 most popular methods: the tick method, the quote method and the Lee and Ready (1991) algorithm. The tick method classification is based on comparing the price of the current trade to the price of the preceding trade. Upticks (price increases) and zero-upticks (zero price changes following the uptick) are classified as buys; downticks (price decreases) and zero-downticks (zero price changes following the downtick) are classified as sells. The main advantages of the method are that only stock price data is required and no trades are left unclassified. However, the algorithm uses less information than the alternative methods. The quote method classifies trades by comparing transaction price to the spread mid-point:

transactions above the mid-quote are considered as buys; below the mid-quote are sells. However, the problem concerning the quote method is that transactions that occur at the mid-point, which account for 15-20% (Odders-White, 2000; Finucane, 2000) or even about 40% (Hasbrouck, 1993) of the total transactions, are left unclassified. Lee and Ready (1991) algorithm is a mixture of both methods: the quote method is applied wherever possible and mid-quote trades are classified using the tick method (Odders-White, 2000).

Factors that are likely to affect the accuracy of classification are: trade location relative to the quoted bid-ask spread, number of crossed and stopped market orders, volatility of quotes and trading prices, size of the company, trading frequency (Finuance, 2000). Other sources of potential errors are off-market crossings being put through at non representative times or data errors.

In practice all of the above mentioned algorithms are used. Following the publication of Lee and Ready in 1991 their suggested algorithm became very popular among researchers investigating price formation and market quality (e.g. Lee (1993), Choi and Subrahmanyam (1994), Brennan and Subrahmanyam (1995, 1998), Harris and Schultz (1997), Cheng and Madhavan (1997)). The quote method among others has been applied by Hasbrouck (1991, 1993), Foster and Viswanathan (1993), Hasbrouck and Sofianos (1993), and Harris, Mclnish and Chakravarty (1995)). The tick method is less popular but still applied in such research as Holthausen, Leftwich and Mayers (1987), Lyons (1995) or Sias and Starks (1997).

The analysis of the trade classification algorithms applicability for the Baltic markets starts with the overview of the trade location relative to quoted spread which is one of the most important determinants of the algorithms' success rate.

Similarly to the developed markets 80% of trades in the Baltics occur at prices equal to the best quoted bid or ask price (Table 2). The key difference is that trades inside the spread that usually account for 15-20% of trades in the developed markets are almost non-existent in the Baltics. In addition, large proportion of trades (15%) in the Baltic markets takes place at prices outside the bid-ask spread (Table 2). Trades outside the spread are much less frequent (around 1%) in more developed markets (Odders-White, 2000; Finucane, 2000). This phenomenon can be explained by low liquidity in the Baltic stock markets as due to thin order books larger trades are likely to have substantial price impact. Trades at the prices lower than bid price are more common than trades at prices higher than ask price.

Across the Baltics Riga has the lowest share of trades that occur at bid or ask prices (72% in Riga versus 82% in Tallinn and Vilnius) and the highest share of trades outside the spread (23% in Riga versus 14% in Tallinn and Vilnius) (Table 2). This is not surprising as Riga is the least active and least liquid market; therefore, due to very thin order books and big price impact more trades are expected to occur at prices outside the spread.

Table 1 in Appendix I illustrates that the similar aforementioned trade frequencies persisted throughout the period 2007-2011. In 2009 the proportion of the trades that occurred at bid-ask prices was the highest (87%), while in 2011 it dropped to 75%.

% of Trades in Trade location category	Tallinn	Vilnius	Riga	Total
Bid	40.1	40.5	37.7	40.2
Ask	42.2	41.7	33.9	41.3
Mid-quote	1.2	1.4	1.2	1.3
Inside spread (Not mid-quote)	3.0	2.6	4.2	2.8
Outside spread (lower)	8.6	8.9	13.5	9.2
Outside spread (higher)	4.9	5.0	9.5	5.3
Number of observations	379,427	858,463	90,039	1,327,929
Quote method misclassified trades (%)	2.4	2.5	2.7	2.5
Tick method misclassified trades (%)	23.9	24.7	31.5	25.0

Table 2. Source: authors' calculations, using data from NASDAQ OMX Group (2012).

Further the accuracy rates of both the tick and the quote method are compared. Note that only automatic trades are included in the analysis and the comparison can be done only for trades where actual direction is known (73% of the sample). The accuracy of the quote method is extremely high (97.5%) while the tick method turns out to be considerably less accurate (75%) (Table 3).

In other research it is commonly found that all the methods perform reasonably well for the transactions at the bid and ask prices or outside the spread (success rate 90%), the accuracy rate for trades inside the spread declines (78%-83%) and transactions that occur at the mid-quote price are the most problematic (total success rate 63%-65%; 77% for mid-quote non-zero ticks and only 60% for mid-quote zero ticks) (Finucane, 2000; Odders-White, 2000).

We find that consistently with previous research the accuracy rate is dependent on the trade location relative to the bid-ask quotes. In our sample the accuracy of the quote method for trades at the quotes and outside the spread is very high (over 99%). The accuracy falls dramatically for trades inside the spread (65% accuracy rate). Trades on the mid-quote cannot be classified by construction of the algorithm (Table 3).

The tick method has lower accuracy rates and accuracy dependence on trade location is even more obvious. Consistently with theory the algorithm is the most accurate for trades outside the spread (over 85%) and slightly less accurate for trades on the bid or ask quotes (75%). In the Baltics tick method is only 50% accurate inside the spread, similar accuracy would be expected if one would toss a coin to classify trades.

% of correctly classified trades	Quote method	Tick method
Bid	99.7	75.9
Ask	99.7	73.6
Mid-quote	0.0	50.2
Inside spread	64.8	47.5
Outside spread (lower)	99.5	85.8
Outside spread (higher)	99.4	88.3
Total	97.5	75.1

Table 3. Source: authors' calculations, using data from NASDAQ OMX Group (2012).

The accuracy of the quote method (about 98%) is considerably higher than the ones reported in previous studies carried on in the developed equity markets (Lee & Ready, 1991; Lee & Radhakrishna, 1996; Aitken & Frino, 1996; Odders-White, 2000, Finucane, 2000). However, there are several factors that explain such a high accuracy rate in the Baltic markets in general and in our sample in particular.

An important reason for trade classification errors in the developed markets are stopped orders and quote improvement provided by dealers that trade at prices between the bid-ask, sometimes on the other side of the mid-quote. As such dealers in the Baltic market do not exist this type errors are eliminated.

In addition, Finucane (2000) provides evidence that classification accuracy decreases when quotes change more frequently. In the Baltic markets quote updates occur infrequently: in our sample the average lag between the last quote update and subsequent trade is 13.5 minutes. Moreover, infrequent trading activity allows obtaining fairly accurate data as merging errors are less likely to occur.

Finally, Finucane (2000) shows that larger spreads are associated with higher accuracy rates. Given that spreads in the Baltics usually are wider than in developed markets this factor could also help explaining higher accuracy rates.

The tick method performance rate is very similar to the ones reported in the developed markets; however, it is considerably lower than the quote method. Relatively worse performance can be caused by the fact that the tick method uses less information than the quote method (Finucane, 2000).

In addition to the market features high accuracy rates are likely to be affected by the sample selection. Non-automatic trades are excluded from our research in this way eliminating one potential source of errors. Accuracy rate for non-automatic trades should be considerably lower as off-market crossings are likely to be reported at non representative times with a delay of up to a couple of days. In addition, we examine only continuous market trades where the trade initiator can be unambiguously identified, i.e. auctions and internalized trades are not included in accuracy evaluation. Therefore, previously reported accuracy rates are valid only for automatic continuous market trades.

To sum up, the quote method turns out to be a very good tool (98% accuracy) suitable to classify automatic continuous market trades in the Baltic markets and other emerging markets that have similar market features (absence of dealers that trade at prices inside the spread, infrequently changing quotes, good electronic platform providing accurate data).

5. Results and discussion

5.1. VAR estimation results

The aggregated results on 6 test specifications can be found in the appendix II. Coefficients of the lagged returns are generally significant across all of the stocks and specifications, although 4-5 lags are insignificant at 5% level for some stocks (cannot be explained merely by a false-negative). Not surprisingly, negative autocorrelation in returns is observed at all lags. Additionally, the magnitude is similar across all models, coefficients on first, second and third lags average between -0.324 and -0.310, -0.159 and -0.133, -0.092 and -0.063 respectively. The magnitude of these coefficients are a lot larger than in the developed markets(e.g. Hasbrouck 1991b). Signed volume, however, tend to be statistically insignificant, especially if not transformed. Logarithmically and square-root compressed signed volumes are significant more often and more so for stocks that have numerous observations. The reason for applying the model for all stock regardless the validity issue was to test the technical performance of the model under different specifications and different sample sizes. It provided a solid ground for the selections of stocks for which consistent quality measures can be obtained.

The results of final specification averaged across stocks can be found in the appendix II. These results are similar to the test specifications. The coefficients vary across time more than they did across specifications. The annual differences between autoregressive coefficients of returns are statistically significant below 1% level for most of the stocks. First, second and third lag autoregressive coefficients vary between -0.301 and -0.277, -0.137 and -0.103, -0.072 and -0.05 respectively. It must be noted that for some stocks the variations between years are higher than the others. This reflects in the quality estimates. The three coefficients mentioned are generally statistically significant at 5% level. The rest of the coefficients are statistically significant only for some of the stocks in several consequent years. The higher lags tend to be statistically significant less frequently.

5.2. Pricing error estimation results

As previously mentioned the dispersion of pricing error with test specifications was calculated for 92 firms. In total, there were 1578490 (1724708) observations on which 5 (3) lag VAR models estimated the coefficients. Effective number of observations varied across stocks considerably, from 150 (315) observations to 209790 (213800) observations for 5 (3) lag models. Since there was a considerable difference in sample sizes, observations were split into four groups accordingly. First group contained stocks with more than 35 thousand effective observations. This group had only 11 stocks, but almost a million total observations, which is approximately two thirds of the total observations available. The rest of the stocks were split into 3 groups (27 stocks in each group) with descending number of observations. The table 8 in Appendix II summarizes the results.

First of all, we review the consistency of the model under different specifications and different sample sizes. We found that for the first two subsample groups the magnitude of the estimates is very similar across specifications but substantially different across subsamples which imply consistency of the estimates. However, the consistency of the dispersion of pricing error among specifications drops significantly in the last group – both the mean and the standard deviation are erratic, especially among the 5 lag specifications. These findings suggest that the model provides consistent estimates for frequently traded stocks; however, it becomes not applicable for inactively traded stocks.

The results suggest that the lower bound of the variance of the pricing error is higher for specifications with more lags. This is consistent with Hasbrouck (1993). Moreover, adding a signed square root of volume into the VAR strengthens the lower bound across all of the subsamples as compared with specifications that contain only the signed volume. However, adding an explanatory variable does not increase the cross-sectional variance of the measure among the stocks – standard deviations of the subsample means are very similar among the two sets of specifications. This implies that cross-sectional studies of market quality are not particularly sensitive to VAR specifications, when using this quality measure.

Turning to the interpretation of the magnitude of the estimated average dispersion of the pricing error it can be noted that the results in first two subsamples are comparable to the ones obtained in other empirical work using similar methodology. For example, Hasbrouck (1993) reported the average estimates varying from 0.153 to 0.552 depending on the market capitalization while our estimates for the first two subsamples vary from 0.177 to 0.390. The estimates for the third subsample group exceeds the ones reported for the developed markets while in fourth sample the magnitude of the estimates explode reaching up to 3.124. Finding that the quality of the relative pricing efficiency increase with more active trading activity is consistent with economic theory as it is expected to be correlated with higher liquidity, tighter bid-ask spread, lower price impact and faster information incorporation into the stock price.

To further visualize the results, stocks were ranked according to estimates obtained using 3 and 5 lag specifications containing the signed square root of volume (see Appendix III). The largest inconsistencies between estimates obtained using different VAR specifications are present for the lowest ranking stocks. Moreover, mismatch seems to be larger between measures obtained using 5 lag VARs. This is least true for stocks with the lowest estimates, therefore the stocks in the high-end of the graphs are not included in further analysis, since the measure fails to rank those firms consistently. It also must be noted that 3 and 5 lag specifications had different effective sample sizes and some differences between different lag length specifications might be attributed to this mismatch.

The results from the main 5 lag specification {r, sign(x), sqrt(x), x} were similar to the previous 6. Only for several stocks from the ones that were used in both, test and main specifications, did the market quality estimates were substantially different. These are the stocks for which VAR coefficients varied year by year the most. It turned out that annual estimation of VAR coefficients considerably increased the estimates of dispersion of pricing error for the aforementioned stocks. After allowing change in VAR coefficients annually we expect that the estimates of the standard deviation of the pricing error are more accurate, especially for stocks with least stable VAR coefficients. The sample of stocks used for this specification includes 22 stocks from Vilnius, only 3 from Riga and 11 stocks from Tallinn stock exchange. These are the stocks that had enough trades per day.

Monthly averages of monthly dispersions of the pricing error across these stocks for Vilnius and Tallinn markets are graphed longitudinally in the appendix III. It must be noted that one should not make any inferences about the overall quality of Vilnius or Tallinn markets from these averages, since sample of stocks is biased towards good quality stocks. The existence of this bias can be easily substantiated with evidence from testing stage specifications – stocks with higher number of total observations tend to have higher market quality. Nevertheless, the averages obtained can be compared over time. Consistently with Čekauskas et al. (2011) any significant market quality improvement over time cannot be indicated. However, the impact of the economic recession on market quality is obvious: in the above mentioned averages one can notice an increase in dispersion of pricing error around the last quarter of year 2008 and convergence back to the historic levels in 2010. This coincides with the resent global economic crunch. Čekauskas et al. (2011) provide evidence that liquidity of the market worsened during the crisis period; however, their findings about informational efficiency were inconclusive. Findings of our research suggest that informational efficiency was affected as well and it substantially worsened during the crisis. Differences in findings can be explained by the fact that in contrast to high-frequency data examined in this research Čekauskas et al. (2011) used daily data; therefore, short lasting inefficiencies could not be captured by their estimates. In addition, as noted in the literature review part, the estimates which turned out to be insignificant in Čekauskas et al. (2011) research are highly sensitive to the time horizons used.

5.3. Institutional trading

Coefficients on all of the counterparty dummies in all of the specifications are statistically significant below 1% level. The coefficients are very similar between specifications. As compared to trades where both counterparties are individuals, trades between institutions have around 21% lower absolute value of pricing errors on average. For trades where an institution is the passive side and an individual is the active side, transactions happen 20-21% closer to the consensus price as compared to trades between individuals. Finally, trades between individuals and institutions where the later is the initiator happen around 7% closer to consensus price as compared to the reference group.

As a robustness check, an interaction term between crisis dummy and trade counterparty dummies were included into all regressions, to check whether the resent global financial turmoil could have influenced the relationships exhibited above. However this was not the case, the regression coefficients on the previously mentioned interaction terms were statistically insignificant at 5% level and the addition of the interaction dummies does not change the rest of the coefficients and standard errors in the regression. This implies that authors have not found evidence in favor of recent financial crisis having a significant effect on the relationships revealed by counterparty dummies in our main regressions.

The main results not only provide evidence that institutional trading activity improves market quality but also allow comparing efficiency of mechanisms that link institutional trading with market quality. The magnitude of coefficients suggests that the most efficient price is set when two institutions are trading with each other. It is consistent with proposition that institutions are more likely to be informed investors than individuals and information revealed by institutional order flow is more likely to be permanently impounded in the stock price (Boehmer & Kelley, 2007; Krustins & Silina, 2011). Therefore, the price two institutions agree on is expected to be closer to the consensus efficient price.

Two dummies indicating trades where both institutional and private investors are involved reveal that trades where institutions take a passive role are related with lower pricing error as compared with trades where institutions take an active role. Passive trade side can be associated with market making, since passive traders post limit orders effectively extending liquidity in the market. The findings are consistent with rationale that institutional traders are superior at identifying informed trading and thus their bid and ask prices track the efficient price closer. If institutions provide enough liquidity, uninformed traders are not able to push the price away from the efficient one (Boehmer & Kelley, 2007). The magnitude of the estimates reveals that institution market making is very important to the quality of the Tallinn stock market as liquidity to uninformed trades reduce temporary price moves not associated with changes in the consensus efficient price. This role of institutional trading is especially important in the Baltic markets that suffer from severe illiquidity.

Even though active institutional trading does not seem to add as much quality as passive institutional trading it is still more quality enhancing than individuals' trading. The difference between active individual trading and active institutional trading is expected from the fact that institutional traders tend to be better informed than the private traders. Institutional traders are expected to trade actively on private information and remove identified stock mispricing in this way bringing prices closer to the efficient consensus price.

The magnitude of the improvement provided by passive institutional trading is economically significant: pricing error decrease by almost one fifth which is significant quality improvement. Findings that passive institutional trading has stronger effect on the market quality as compared with active institutional trading and the relative magnitude of the effects (passive institutional trading improves quality 3 times more than active) are highly comparable with the ones reported by Boehmer & Kelley (2007).

5.4. Experience

Since the regressions take log-log design, the interpretation of the coefficients take a typical learning curve interpretation –percentage change in the dependent variable due to 100% change in independent variable. In the regressions with both institutional and individual trades coefficients on all experience proxies are significant at 5% level. Cumulative number of trades and cumulative volume traded seem to have similar effects on market quality. After doubling the cumulative amount of trades the trader is expected to trade 0.93% closer to consensus price. Have in mind that the lower bound of the standard deviation of the pricing error lies at around 0.18-0.67% of stock price in the present sample. Therefore, smaller than one percent reduction of that fraction is not economically significant and does not constitute a steep learning curve. Similar result is present for cumulative volume traded. One expects a 0.76% lower absolute percentage value of the pricing error with every doubling of cumulative volume traded. Interaction terms between institutional dummy and cumulative number of trades as well as cumulative volume traded are negative but statistically insignificant, suggesting that there are no significant differences between institutional and individual learning. On one hand we would expect that traders that work for institutions are in better learning environment in a sense that they have access to more information and learning tools as well as can benefit from information pooling. On the other hand, institutional traders are expected to have lower marginal learning effects, since the aggregate experience is expected to be higher– institutions tend to select more experienced individuals as well as devote recourses to spur learning. For regressions that include only individual traders, coefficients for cumulative number of trades and volume traded suggest that doubling in these variables would result in trades being closer to consensus price than average by 0.78% and 0.75% respectively. These coefficients are similar to the ones in full sample regressions and seem to be economically insignificant.

Some of the most puzzling results are the positive regression coefficients for the days of experience. These coefficients remain positive and statistically significant at 5% level even when controlling for wealth, average trade size, age and time (in a form of monthly dummies). All four regressions report similar coefficients – doubling the amount of time one has traded in the Estonian stock exchange is expected to result in one trading 1.2-1.4% further away from the consensus price in the market. Even though statistically significant, the relation does not seem to be economically important.

All the measures used in the analysis suffer from certain limitations and can be perceived as noisy measures of traders' experience. The most severe limitation is the fact that data is available only for Estonian stock market meaning that any experience gained in other securities' markets is not directly captured by the estimates. Another factor that might affect accuracy of the experience measurement is censoring of the experience variables due to dataset providing data only from year 2004. However, this bias is expected to be mitigated by a 3 year lag (2004-2006) not included in the regression analysis. In addition, as robustness check in non-reported regressions we run all four specifications including a dummy which indicates if the experience variable is subject to censoring. The dummy turns out to be statistically insignificant and results remain almost identical.

To sum up, there exist evidence that trading experience gained via more intense trading activity lead to better market quality; however, the impact is economically insignificant. In contrast, experience measure which depends purely on time provides opposite results. As measures directly related with trading activity (cumulative number of trades and value traded) should be more correlated with hands-on experience they should be perceived as more valid experience measures. The results based on these measures provide evidence that experienced traders tend to improve market quality.

5.5. Control variables

The coefficients on average trade size are statistically significant (below 1% level) in all of the regressions and are negative. This is expected if average trade size is highly correlated with informed trading. To recover the fixed costs of information acquisition one must trade in higher volumes. The regression coefficients imply that doubling in the average trading volume is associated with trading at price 9.8-10.5% closer to the consensus value for individuals and 5.96 – 7.16% closer for institutions. Interaction term between institutional dummy and average trade volume is positive and statistically significant at 1%. If the average trading volume is in fact correlated with informed trading, informational asymmetries would be expected to be higher between individuals than between institutions. Thus same increase (in percentage terms) in average trading volume for an individual might indicate a higher increase in relative informativeness (as compared to other individuals) than for institution (as compared to other institutions). Also institutions have significantly higher average trading volume than the individuals. This means that the average pricing impact (which is captured by the pricing error) is expected to be higher for institutions resulting in negative effect on market quality. Combination of average trade size being correlated with informed trading and price impact could explain the regression coefficient being higher (in absolute terms) for individuals compared to institutions.

Regression results suggest that there are no statistically significant differences between local and foreign individual investors' trading effects on market quality. In contrast, foreign institutions tend to trade at the price 7.8% further from consensus efficient price as compared with local institutions. This phenomenon can be explained by the fact that local institutions on average tend to be more informed about Estonian market specifics.

Consistently with expectations and findings reported by Hasbrouck (1993) market quality turn out to worsen during the opening and closing half an hour of the trading day. The coefficient on Opening dummy is significant at 5% significance level in a full sample regression and at 1% in the regressions that include only individuals. Closing dummy is significant at 1% level in full sample regression and insignificant in regression for individuals. Results are economically significant as trades at the opening half an hour are expected to occur at the price 6.7% further from consensus efficient price for the full sample and 10.8% further for individuals as compared with trades in the middle of the trading day. Last half an hour is associated with 6.5% higher magnitude of the pricing error as compared to the mid-day trades for a full sample. Higher divergence from the consensus efficient price at the last half an hour of trading is likely to be driven by institutional investors as the effect for individuals is not statistically significant. This decrease in market quality can be associated with institutional traders willing to close their positions in order not to be exposed to overnight risk as well as increase in market manipulation at the end of the trading day which was reported by Comerton-Forde and Putniņš (2011).

6. Conclusions

The aim of this paper is to investigate the quality of the Baltic equity markets. We test and use a summary measure of market quality, which indicates how closely transaction prices follow the consensus efficient price. In addition we have augmented the original methodology developed by Hasbrouck (1993) with formula suggested by Arino and Newbold (1998). Augmentation results in more accurate estimates of the pricing error as well as makes the methodology applicable to more stocks in the markets with low number of daily trades, such as the Baltic equity market. To further provide methodological guidelines for computation of the summary quality measure the accuracy of trade classification algorithms into buyer and seller initiated trades was investigated. In the Baltic equity markets the quote method is almost 98% accurate for automatic continuous market trades, while success rate for tick method is considerably lower (approximately 75%). These results are very important for all micro-level research in the Baltics or other emerging markets that relies on trade classification.

After computing the summary quality measure we proceed with trader level analysis of the determinants of the market quality. The analysis shows that institutions improve market quality via market making and informed trading, the former being the most important channel. The effects on market quality are economically significant. Institutions are able to recognize the informed traders and post limit orders around consensus efficient price, effectively extending liquidity in the market and preventing more pronounced pricing errors. This is consistent with previous empirical research such as work by Boehmer and Kelley (2007) in NYSE. The implication of these findings for policy makers and regulators is that if they are interested in market quality improvement, passive institutional trading should be incentivized.

Though economically insignificant, there is some evidence on trader experience increasing market quality in the Tallinn stock exchange. The traders experience is related to their ability to recognize informed traders, learn their signals quicker as well as be more able to recognize and account for various market manipulations. These results are consistent with findings obtained in laboratory or experimental markets (Ketcham, Smith & Williams, 1984; Lundholm, 1991; Cason & Friedman, 1997). However, our study suggests the effects of traders' experience being less pronounced than in the aforementioned research.

There are a number of suggestions for further research. First, since there were changes in the transaction currency in the Vilnius stock exchange as well as adoption of Euro in Estonia an investigation of structural breaks would unveil the effects of these events on market quality. Second, major news announcements such as earnings releases or annual financial statements tend to reduce the informational asymmetries and are expected to increase the market quality. On the other hand, such news events result in more trading that drains liquidity in the market. Empirical investigation of such events would give valuable insights on the dominance of these two effects. Third, investigation of popularity of firms in internet search engines as well as popularity in the news in context of market quality would shine light on the link between fads, noise trading and market quality. Finally, investigation of accounting quality and earnings report manipulation would better describe markets resiliency to these factors.

7. References

Aitken, M. & Frino, A., (1996). The accuracy of the tick test: evidence from the Australian stock exchange. Journal of Banking and Finance, 20, 1715-1729.

Albanesi, S. & Rindi, B. (2000). The Quality of the Italian Treasury Bond Market, Asymmetric Information and Transaction Costs. *Annals of Economics and Statistics*, 60, 1-19.

Arino, M. A., & Newbold, P. (1998). Computation of the Beveridge–Nelson decomposition for multivariate economic time series. *Economics Letters 61* , 37–42.

Barclay, M.J. (1997). Bid–ask Spreads and the Avoidance of Odd-eighth Quotes on NASDAQ: An Examination of Exchange Listings. *Journal of Financial Economics* 45, 35–60.

Barclay, M.J., Christie, W.G., Harris, J.H., Kandel, E., & Schultz, P.H., (1999). Effects of market reform on the trading costs and depths of Nasdaq stocks. *Journal of Finance*, 54, 1–34.

Barnea, A., (1974). Performance Evaluation of New York Stock Exchange Specialists. *Journal of Financial and Quantitative Analysis*, 9, 511-535.

Bartov, E., Radhakrishnan, S., & Krinsky, I., (2000). Investor sophistication and patterns in stock returns after earnings announcements. *The Accounting Review*, 75, 43-63.

Beebower, G. (1989). Evaluating transaction costs. In: Wagner, W.H. (Ed.), The Complete Guide to Securities Transactions: Enhancing Investment Performance and Controlling Cost. Wiley, New York.

Benston, G.J., & Hagerman, R.L. (1974). Determinants of bid–asked spreads in over-the-counter market. *Journal of Financial Economics*, 1, 353–364.

Berkowitz, S. A., Logue, D. E., & Noser, E. A. (1988). The Total Cost of Transactions on the NYSE. *The Journal of Finance*, 43 (1), 97-112

Beveridge, S. & Nelson, C. R. (1981). A New Approach to Decomposition of Economic Time Series into Permanent and Transitory Components with Particular Attention to Measurement of the 'Business Cycle'. *Journal of Monetary Economics*, 7, 151-174.

Blume, M., & Goldstein, M. (1992). Displayed and effective spreads by market (NBER working paper). Wharton Business School, University of Pennsylvania.

Boehmer, E., & Kelley, E. (2007). Institutional investors and the informational efficiency of prices. Chicago Meetings Paper .

Boehmer, E., Saar, G., & Lei, Y. (2005). Lifting the Veil: An Analysis of Pre-Trade Transparency at the NYSE. The Journal of Finance, Vol. 60, No. 2 , 783-815.

Box, G. E., & Jenkins, G. M. (1968). Some Recent Advances in Forecasting and Control. Journal of the Royal Statistical Society. Series C (Applied Statistics), Vol. 17, No. 2 , 91-109.

Branch, B., & Freed, W. (1977). Bid–ask spreads on the AMEX and the bid board.. *Journal of Finance*, 32, 159–163.

Breen, W. J., Hodrick, L. S., & Korajczyk, R. A. (2002). Predicting Equity Liquidity. *Management science*, 48 (4), 470-483.

Brennan, M. J., & Subrahmanyam, A. (1995). Investment Analysis and Price Formation in Securities Markets. Journal of Financial Economics, 38 (1995), 361-381.

Brennan, M. J., & Subrahmanyam, A. (1996). Market Microstructure and Asset Pricing: On the Compensation for Illiquidity in Stock Returns. *Journal of Financial Economics*, 41, 441-464

Brennan, M. J., & Subrahmanyam, A. (1998). The Determinants of Average Trade Size. Journal of Business, 71, 1-25.

Cason, T. N. & Friedman, D. (1997). Price Formation in Single Call Markets. *Econometrica,* 65 (2), 311-345.

Čekauskas, K., Gerasimovs, R., Liatukas, V. & Putniņš, T. J. (2011). The Effects of Market Makers and Stock Analysts in Emerging Markets. *International Review of Finance*

Cheng, M. & Madhavan, A. (1997). In Search of Liquidity: Block Trades in the Upstairs and Downstairs Markets. Review of Financial Studies, 10, 175-203.

Choi, H., & Subrahmanyam, A. (1994). Using Intraday Data to Test for Effects of Index Futures on the Underlying Stock Markets. Journal of Futures Markets, 14, 293-322.

Christie, W.G., & Huang, R.D. (1994). Market structures and liquidity: A transactions data study of exchange listings. *Journal of Financial Intermediation* 3, 300–326.

Christie, W.G., & Schultz, P. (1994). Why do NASDAQ market makers avoid odd-eighth quotes? *Journal of Finance,* 49, 1813–1840.

Comerton-Forde, C. & Putniņš, T. (2011). Measuring closing price manipulation. *Journal of Financial Intermediation*, 20 (2), 135–158.

Demsetz, H. (1968). The Cost of Transacting. *Quarterly Journal of Economics*. 82 (1), 33-53

Ellis, K., Michaely, R., & O'Hara, M. (2000). The Accuracy of Trade Classification Rules: Evidence from Nasdaq. *The Journal of Financial and Quantitative Analysis*, 35 (4), 529-551.

Engle, R. F., & Lange, J. (2001). Predicting VNET: A model of the dynamics of market depth. *Journal of Financial Markets*, 4, 113-142.

Fama, E. F. & French, K. R. (1988). Permanent and temporary components of stock prices, *Journal of Political Economy*, 96, 246-273.

Finucane, T. J. (2000). A Direct Test of Methods for Inferring Trade Direction from Intra-Day Data. The Journal of Financial and Quantitative Analysis, 35 (4), 553-576.

Fleming, M. J. (2003). Measuring Treasury Market Liquidity. FRB of New York Staff Report No. 133

Forsythe, R. & Lundholm, R. (1990). Information Aggregation in an Experimental Market. *Econometrica*, 58 (2), 309-347.

Foster, F. D., & Viswanathan, S. (1993). Variations in Trading Volume, Return Volatility, and Trading Costs: Evidence on Recent Price Formation Models. Journal of Finance, 48, 187-211.

Grossman, S. J., & Miller, M. H. (1988). Liquidity and Market Structure. *The Journal of Finance,* 43 (3), 617-633

Harris, F. H. deB., Mclnish, T. H. & Chakravarty, R. R. (1995). Bids and Asks in Disequilibrium Microstructure: T he Case of IBM. Journal of Banking and Finance, 19, 323-345.

Harris, J. H., & Schultz, P. H. (1997). The Importance of Firm Quotes and Rapid Executions: Evidence from the January 1994 SOES Rules Change. Journal of Financial Economics, 45, 135-166.

Harvey, A. C. (1985). Trends and Cycles in Macroeconomic Time Series. Journal of Business and Economic Statistics 3 , 216-227.

Hasbrouck J. (1993). Assessing the Quality of a Security Market: A New Approach to Transaction-Cost Measurement". *The Review of Financial Studies*, 6 (1), 191-212.

Hasbrouck J. (1995). Modeling Market Microstructure Time Series. *Handbook of Statistics*, 14, 647-692.

Hasbrouck, J. (1988). Trades, Quotes, Inventories and Information. *Journal of Financial Economics*, 22, 229-252.

Hasbrouck, J. (1991). The Summary Informativeness of Stock Trades: An Econometric. *The Review of Financial Studies*, 4 (3), 571-595

Hasbrouck, J. (1993). Assessing the Quality of a Security Market: A New Approach to Transaction- Cost Measurement. *The Review of Financial Studies*, 6(1), 191-212.

Hasbrouck, J. (2002). Stalking the "Efficient Price" in Market Microstructure Specifications: An Overview. Journal of Financial Markets 5 , 329–339.

Hasbrouck, J., & R. A. Schwartz, (1988). An Assessment of Stock Exchange and Over-the-Counter Markets. *Journal of Portfolio Management*, 14, 10-16.

Hasbrouck, J., & Sofianos, G. (1993). The Trades of Market Makers: An Empirical Analysis of NYSE Specialists. Journal of Finance, 48, 1565-1593.

Hodrick, R., & Prescott, E. C. (1997). Post-war U. S. business cycles: An empirical investigation. Journal of Money Credit and Banking 29(1) , 1-16.

Holthausen, R.W., Leftwich, R.W., & Mayers, D. (1987). The effect of large block transactions on security prices: A cross-sectional analysis. Journal of Financial Economics, 19, 237–267.

Hotchkiss, E. S., & Ronen, T. (2002). The Informational Efficiency of the Corporate Bond Market: An Intraday Analysis. The Review of Financial Studies, Vol. 15, No. 5 , 1325-1354.

Huang, R., & Stoll, H. R. (1997). The components of the bid–ask spread: a general approach. Review of Financial Studies 10 , 995–1034.

Huang, R.D., & Stoll, H.R. (1996a). Competitive trading of NYSE listed stocks: Measurement and interpretation of trading costs. *Financial Markets, Institutions and Instruments*, 5 (2), 1–55.

Huang, R.D., & Stoll, H.R. (1996b). Dealer versus auction markets: A paired comparison of execution costs on NASDAQ and the NYSE. *Journal of Financial Economics,* 41, 313–357.

Ketcham, J., Smith, V. L., & Williams, A. W. (1984). A Comparison of Posted-Offer and Double-Auction Pricing Institutions. *The Review of Economic Studies*, 51 (4), 595-614.

Krishnamurti, C., Sequeira, J. M., & Fu, F. (2003). Stock exchange governance and market quality. *Journal of Banking & Finance,* 27, 1859–1878.

Krustiņš, K., & Siliņa, Z. (2011). Cross-market and Micro-level Price Discovery in the Baltic Stock Markets. *SSE Riga Student Research Papers*

Kyle, A. S. (1985). Continuous Auctions and Insider Trading. *Econometrica*, 53 (6), 1315-1335

Lee, C. M. C. & Radhakrishna, B. (1996). Inferring investor behavior: evidence from TORQ data. University of Michigan working paper.

Lee, C. M. C., & Ready, M. (1991). Inferring trade direction from intradaily data. *Journal of Finance* 46, 733-746.

Lee, C. M. C., (1993), Market fragmentation and price-execution in NYSE-listed securities. *Journal of Finance*, 48, 1009-1038

Lo, A.W. & MacKinlay, A.C. (1988). Stock prices do not follow a random walk: Evidence from a simple specification test. *Review of Financial Studies,* 1, 41-66.

Lundholm, R. J. (1991). What Affects the Efficiency of a Market? Some Answers from the Laboratory. *The Accounting Review*, 66 (3), 486-515.

Lyons, R. K. (1995). Tests of MicrostructuraHl ypotheses in the Foreign Exchange Market. Journal of Financial Economics, 39, 321-351.

Maravall, A. (1995). Unobserved components in economic time series. In H. P. M.R.Wickens, Handbook of Applied Econometrics Vol. 1. Blackwell Press.

Morley, J. C. (2009). The Two Interpretations of the Beveridge-Nelson Decomposition. Macroeconomic Dynamics (2010) , 1-21.

Nasdaq OMX Vilnius (2010). *Trading and settlement currency change in Vilnius, tick size change in the Baltics.* Retrieved on 19 February, 2012 from: http://www.nasdaqomxbaltic.com/market/?pg=news&news_id=245306

Nelson, C. R. (2008). The Beveridge-Nelson Decomposition in Retrospect and Prospect. Journal of Econometrics Volume 146, Issue 2 , 202-206.

Odders-White, E. R. (2000). On the occurrence and consequences of inaccurate trade classifcation. *Journal of Financial Markets*, 3, 259-286.

Oliven, K. & Rietz, T. A. (2004). Suckers Are Born but Markets Are Made: Individual Rationality, Arbitrage, and Market Efficiency on an Electronic Futures Market. *Management Science*, 50 (3), 336–351.

Poterba, J. M. & Summers, L. H. (1988). Mean reversion in stock prices: Evidence and implications. *Journal of Financial Economics*, 22, 27-60.

Sias, R. W., & Starks, L. T. (1997). Institutions and Individuals at the Turn-of-the-Year. *Journal of Finance*, 52, 1543-1562.

Sias, R. W., Starks, L., & Titman, S. (2006). Changes in institutional ownership and stock returns: Assessment and methodology. *Journal of Business*, 79, 2869-2910.

Watson, M. W. (1986). Univariate detrending methods with stochastic trends. *Journal of Monetary Economics*, 18 , 49-75.

8. Appendix I: Descriptive statistics

Table 1: Summary statistics of trades' location relative to the quoted spread and accuracy of trades' classification methods.

The table presents distribution of trades location relative to the quoted bid-ask spread for all automatic continuous market trades (exclude non-automatic trades and auctions) during the period April 2007 – December 2011 for all stocks listed in the Baltic stock exchanges (Nasdaq OMX Vilnius, Riga and Tallinn) and having at least 1000 transactions during the full sample period. Trades' location is identified by comparing trade price with the best bid and ask prices that were prevailing prior the trade: Bid – trades that occurred at the price equal to the quoted bid, Ask – trades that occurred at the price equal to ask price, Mid-quote – trades that occurred at the price equal to the mid-point value between bid and ask prices, Inside spread – trades that occurred at price between posted bid and ask prices but not on the mid-quote, Outside spread (lower) - trades that occurred at price lower than the quoted bid price, Outside spread (higher) - trades that occurred at price higher than the quoted ask price. Accuracy of the quote classification algorithms is identified by comparing estimates obtained using certain algorithm with actual trade initiator information.

% of Trades in Trade location category	**2007**	**2008**	**2009**	**2010**	**2011**
Bid	41.3	41.0	40.7	40.0	36.7
Ask	39.3	40.2	45.8	42.7	37.7
Mid-quote	0.9	0.8	1.2	2.4	1.1
Inside spread	2.7	2.1	1.3	3.4	4.8
Outside spread (lower)	10.2	10.6	6.6	7.2	12.5
Outside spread (higher)	5.7	5.2	4.5	4.3	7.3
Number of observations	207,891	280,617	295,813	315,216	228,392
Quote method misclassified trades (%)	1.9	1.5	1.6	4.3	3.0
Tick method misclassified trades (%)	25.5	25.5	23.2	23.4	28.3

Source: authors' calculations, using data from NASDAQ OMX Group (2012).

Table 2: Summary statistics of trades' classification by the type of counterparties

The table provides descriptive statistics of the sample used for the regression analysis. Only trades where the type (private or institutional trader) of both counterparties is known are included. There are four types of trades by the combinations of trader groups: trades that involve two institution (1), trades where private investors are active traders and institutions are passive counterparties (2), trades where institutions are active traders and private investors are passive liquidity providers (3), trades that involve two individual traders (4).

	Frequency	**Percent**
Institution (active) - Institution (passive)	42,684	26.71
Private (active) - Institution (passive)	34,044	19.79
Institution (active) - Private (passive)	31,626	21.30
Institution (active) - Private (passive)	51,466	32.20
Total	159,820	100

Source: authors' calculations, using data from NASDAQ OMX Group (2012).

Table 3: Summary statistics of investors' characteristics

Summary statistics calculated for the investors included in the sample of the regression analysis. Summary statistics is provided separately for individual (Panel A) and institutional (Panel B) investors. Nr of trades - experience as a cumulative number of trades that investor has made during one's trading period in the Tallinn stock exchange. Traded volume – cumulative value of trades that investor has made during one's trading period in the Tallinn stock exchange. Months of experience - cumulative number of trading months since the registration of the portfolio in the Tallinn stock exchange. Wealth – average size of trader's portfolio recalculated on yearly basis, Average trade – average value of trader's transaction recalculated on yearly basis, Age – age of individual measured in years, Foreigners – percent of foreign traders in our sample, Male – percent of male traders in our sample. Information about age and gender are available only for individuals.

Panel A: Individual investors

Sample size ≈ 84,000	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Nr of trades	223	590	0	5,445
Traded volume	407,163	1,165,876	0	10,942,172
Months of experience	30.4	22.8	0	83
Wealth	18,361	49,941	0	4,872,434
Average trade	1,347	1,226	0.13	48,917
Age (years)	39.58	13.05	8	106
Foreigners (%)	10.7%			
Male (%)	84.6%			

Panel B: Institutional investors

Sample size ≈ 75,000	**Mean**	**Std. Dev.**	**Minimum**	**Maximum**
Nr of trades	27,437	35,384	0	112,091
Traded volume	269,503,890	333,909,451	0	935,809,536
Months of experience	43.5	23.8	0	83
Wealth	3,605,533	6,118,447	0	21,556,230
Average trade	4,472	3,454	3.16	75,000
Foreigners (%)	8.9%			

Source: authors' calculations, using data from NASDAQ OMX Group (2012).

9. Appendix II: Estimation results

Table 4: VAR output of test specifications

This table presents average VAR output over 92 stocks. Standard deviations of the averages are in the parentheses. Only the first VAR equation is presented in which trade returns are the dependant variable. First column specifies the left hand side variables and their lags. First row gives the explanatory variables and lag length used in VAR in parentheses. Column "% of p-values < 0.05" gives the fraction of 92 coefficients that were statistically significantly different from zero at 5% level.
r – intraday stock returns between subsequent trades
x – trade volume, signed positive if the trade was identified as buyer-initiated and negative if identified as seller-initiated. Unclassified trades have a value of zero.

Specification	**Signed volume (3 lags)**			**Signed volume (5 lags)**		
	Avg. R-squared = 10.1%		Avg # of obs. (Std. Dev.) = 17914 (31483)	Avg. R-squared = 11.8 %		Avg # of obs. (Std. Dev.) = 16463 (30545)
Independent variable	Avg. coeff. (Std. Dev.)	Avg. SE (Std. Dev.)	% of p-values < 0.05	Avg. coeff. (Std. Dev.)	Avg. SE (Std. Dev.)	% of p-values < 0.05
l.r	-0.310 (0.072)	0.018 (0.016)	100	-0.314 (0.081)	0.023 (0.026)	98.91
l2.r	-0.133 (0.060)	0.019 (0.016)	92.39	-0.152 (0.078)	0.023 (0.024)	88.04
l3.r	-0.063 (0.040)	0.017 (0.015)	76.08	-0.088 (0.092)	0.022 (0.021)	77.17
l4.r	-	-	-	-0.042 (0.065)	0.022 (0.023)	67.39
l5.r	-	-	-	-0.012 (0.046)	0.020 (0.020)	46.74
l.x	4.846E-07 (2.033E-06)	5.872E-07 (1.779E-06)	13.04	1.396E-07 (3.654E-06)	7.800E-07 (2.505E-06)	14.13
l2.x	5.769E-07 (3.401E-06)	5.628E-07 (1.691E-06)	7.61	1.116E-06 (6.111E-06)	8.016E-07 (2.525E-06)	9.78
l3.x	-6.525E-07 (4.555E-06)	5.681E-07 (1.715E-06)	9.78	-3.775E-07 (3.152E-06)	7.425E-07 (2.237E-06)	6.52
l4.x	-	-	-	-4.626E-07 (3.908E-06)	7.095E-07 (2.211E-06)	5.43
l5.x	-	-	-	3.540E-07 (5.689E-06)	7.433E-07 (2.200E-06)	7.61

Source: authors' calculations, using data from NASDAQ OMX Group (2012).

Table 5: VAR output of test specifications

This table presents average VAR output over 92 stocks. Standard deviations of the averages are in the parentheses. Only the first VAR equation is presented in which trade returns are the dependant variable. First column specifies the left hand side variables and their lags. First row gives the explanatory variables and lag length used in VAR in parentheses. Column "% of p-values < 0.05" gives the fraction of 92 coefficients that were statistically significantly different from zero at 5% level.
r – intraday stock returns between subsequent trades
ln(x) – logarithmically compressed signed trade volume.

Specification	**Log-compressed signed volume (3 lags)**			**Log-compressed signed volume (5 lags)**		
	Avg. R-squared = 10.2%		Avg # of obs. (Std. Dev.) = 17914 (31483)	Avg. R-squared = 11.8%		Avg # of obs. (Std. Dev.) = 16463 (30545)
Independent variable	Avg. coeff. (Std. Dev.)	Avg. SE (Std. Dev.)	% of p-values < 0.05	Avg. coeff. (Std. Dev.)	Avg. SE (Std. Dev.)	% of p-values < 0.05
l.r	-0.320 (0.075)	0.019 (0.016)	100	-0.324 (0.084)	0.024 (0.027)	98.91
l2.r	-0.138 (0.060)	0.020 (0.017)	93.48	-0.159 (0.080)	0.024 (0.024)	91.30
l3.r	-0.064 (0.041)	0.018 (0.015)	77.17	-0.092 (0.096)	0.024 (0.022)	76.09
l4.r	-	-	-	-0.045 (0.066)	0.024 (0.024)	67.39
l5.r	-	-	-	-0.015 (0.048)	0.021 (0.021)	45.65
l.ln(x)	0.000131 (0.000222)	8.944E-05 (0.000151)	59.78	0.000121 (0.000225)	0.000106 (0.000189)	56.52
l2. ln(x)	3.075E-05 (0.000232)	0.000097 (0.000165)	33.70	5.647E-05 (0.000343)	0.000115 (0.000206)	31.52
l3. ln(x)	-6.734E-05 (0.000295)	8.779E-05 (0.000148)	25	-2.469E-05 (0.000165)	0.000115 (0.000207)	11.96
l4. ln(x)	-	-	-	-1.499E-05 (0.000192)	0.000115 (0.000205)	8.70
l5. ln(x)	-	-	-	6.324E-06 (0.000155)	0.000103 (0.000183)	9.78

Source: authors' calculations, using data from NASDAQ OMX Group (2012).

Table 6: VAR output of test specifications

This table presents average VAR output over 92 stocks. Standard deviations of the averages are in the parentheses. Only the first VAR equation is presented in which trade returns are the dependant variable. First column specifies the left hand side variables and their lags. First row gives the explanatory variables and lag length used in VAR in parentheses. Column "% of p-values < 0.05" gives the fraction of 92 coefficients that were statistically significantly different from zero at 5% level.

r – intraday stock returns between subsequent trades

x – trade volume, signed positive if the trade was identified as buyer-initiated and negative if identified as seller-initiated. Unclassified trades have a value of zero.

sqrt(x) – square root of trade volume signed analogically to *x*.

Specification	**Signed square root of volume and signed volume (3 lags)**			**Signed square root of volume and signed volume (5 lags)**		
	Avg. R-squared = 10.4%		Avg # of obs. (Std. Dev.) = 17915 (31483)	Avg. R-squared = 12.4%		Avg # of obs. (Std. Dev.) = 16463 (30545)
Independent variable	Avg. coeff. (Std. Dev.)	Avg. SE (Std. Dev.)	% of p-values < 0.05	Avg. coeff. (Std. Dev.)	Avg. SE (Std. Dev.)	% of p-values < 0.05
l.r	-0.318 (0.074)	0.019 (0.016)	100	-0.323 (0.082)	0.082 (0.027)	98.91
l2.r	-0.139 (0.061)	0.019 (0.017)	93.48	-0.159 (0.081)	0.024 (0.024)	90.22
l3.r	-0.064 (0.040)	0.018 (0.015)	75	-0.092 (0.095)	0.023 (0.022)	76.09
l4.r	-	-	-	-0.047 (0.063)	0.023 (0.024)	69.57
l5.r	-	-	-	-0.015 (0.044)	0.021 (0.020)	45.65
l.sqrt(x)	4.904E-05 (0.000114)	4.286E-05 (9.772E-05)	47.83	6.142E-05 (0.000218)	5.279E-05 (0.000121)	46.74
l2.sqrt(x)	1.318E-05 (6.642E-05)	4.494E-05 (0.000105)	15.22	9.032E-06 (0.000208)	5.751E-05 (0.000136)	17.39
l3.sqrt(x)	-1.404E-05 (0.000120)	4.271E-05 (9.906E-05)	14.13	1.364E-05 (0.000144)	5.674E-05 (0.000134)	3.26
l4.sqrt(x)	-	-	-	3.466E-06 (0.000167)	5.421E-05 (0.000130)	8.70
l5.sqrt(x)	-	-	-	-6.223E-07 (0.000148)	5.273E-05 (0.000122)	13.04
l.x	-6.768E-07 (2.810E-06)	1.210E-06 (3.710E-06)	21.74	-1.864E-06 (1.312E-05)	1.598E-06 (4.924E-06)	25
l2.x	6.089E-08 (2.879E-06)	1.190E-06 (3.730E-06)	13.04	6.848E-07 (8.952E-06)	1.732E-06 (5.423E-06)	13.04
l3.x	-3.780E-07 (6.402E-06)	1.205E-06 (3.790E-06)	10.87	-9.354E-07 (7.475E-06)	1.588E-06 (4.811E-06)	6.52
l4.x	-	-	-	-7.213E-07 (8.647E-06)	1.500E-06 (4.837E-06)	5.43
l5.x	-	-	-	1.951E-07 (9.267E-06)	1.593E-06 (4.780E-06)	6.52

Source: authors' calculations, using data from NASDAQ OMX Group (2012).

Table 7: Annual VAR output of the final specification.

Panel A

This table presents average VAR output over 36 stocks. VAR was estimated for each stock and each year separately. The year is indicated in the first row of the table. Standard deviations of the averages are in the columns to the right of the averaged statistic. Only the first VAR equation is presented in which trade returns are the dependant variable. First column specifies the left hand side variables and their lags. Column "% of p-values < 0.05" gives the fraction of 36 coefficients that were statistically significantly different from zero at 5% level.
r – intraday stock returns between subsequent trades
sign(x) – trade sign that takes value of 1 if trade is buyer initiated, -1 if the trade is seller initiated and 0 if the trade was unclassified.
x – trade volume, signed positive if the trade was identified as buyer-initiated and negative if identified as seller-initiated. Unclassified trades have a value of zero.
sqrt(x) – square root of trade volume signed analogically to *x*.

Year			**2007**		
	Avg. R-squared = 10.7%			Avg # of obs.(Std. Dev.) = 4030 (3944)	
Independent variable	Avg. coeff.	(Std. Dev.)	Avg. SE	(Std. Dev.)	% of p-values < 0.05
l.r	-0.3032	0.0926	0.0256	0.0139	100.0
l2.r	-0.1366	0.0779	0.0266	0.0145	93.5
l3.r	-0.0669	0.0555	0.0264	0.0145	71.0
l4.r	-0.0404	0.0403	0.0252	0.0136	45.2
l5.r	-0.0202	0.0204	0.0225	0.0123	22.6
l.sign(x)	-0.0001	0.0012	0.0005	0.0007	22.6
l2. sign(x)	-0.0003	0.0007	0.0005	0.0007	19.4
l3. sign(x)	-0.0001	0.0007	0.0005	0.0007	12.9
l4. sign(x)	-0.0002	0.0009	0.0005	0.0007	22.6
l5. sign(x)	0.0003	0.0009	0.0005	0.0007	0.0
l. sqrt(x)	5.34E-06	2.20E-05	2.07E-05	4.22E-05	12.9
l2. sqrt(x)	1.70E-05	4.52E-05	2.09E-05	4.27E-05	19.4
l3. sqrt(x)	-6.96E-06	3.20E-05	2.07E-05	4.25E-05	19.4
l4. sqrt(x)	5.03E-06	2.15E-05	2.09E-05	4.42E-05	12.9
l5. sqrt(x)	-9.60E-06	3.63E-05	2.12E-05	4.48E-05	0.0
l.x	-3.11E-08	2.10E-07	2.01E-07	5.04E-07	12.9
l2.x	-5.72E-08	4.40E-07	2.03E-07	5.13E-07	16.1
l3.x	2.25E-07	7.34E-07	2.04E-07	5.21E-07	9.7
l4.x	5.33E-08	3.58E-07	2.02E-07	5.23E-07	6.5
l5.x	6.54E-08	4.33E-07	2.10E-07	5.41E-07	3.2

Source: authors' calculations, using data from NASDAQ OMX Group (2012).

Panel B

This table presents average VAR output over 36 stocks. VAR was estimated for each stock and each year separately. The year is indicated in the first row of the table. Standard deviations of the averages are in the columns to the right of the averaged statistic. Only the first VAR equation is presented in which trade returns are the dependant variable. First column specifies the left hand side variables and their lags. Column "% of p-values < 0.05" gives the fraction of 36 coefficients that were statistically significantly different from zero at 5% level.
r – intraday stock returns between subsequent trades
sign(x) – trade sign that takes value of 1 if trade is buyer initiated, -1 if the trade is seller initiated and 0 if the trade was unclassified.
x – trade volume, signed positive if the trade was identified as buyer-initiated and negative if identified as seller-initiated. Unclassified trades have a value of zero.
sqrt(x) – square root of trade volume signed analogically to *x*.

Year	**2008**				
	Avg. R-squared = 9.1%		Avg # of obs.(Std. Dev.) = 4910 (7099)		
Independent variable	Avg. coeff.	(Std. Dev.)	Avg. SE	(Std. Dev.)	% of p-values < 0.05
l.r	-0.2767	0.0762	0.0282	0.0153	100.0
l2.r	-0.1025	0.0659	0.0288	0.0156	72.7
l3.r	-0.05	0.0528	0.0284	0.0154	51.5
l4.r	-0.0205	0.0431	0.0274	0.0147	21.2
l5.r	-0.0175	0.0454	0.025	0.0135	21.2
l.sign(x)	0.0001	0.002	0.0008	0.0007	21.2
l2. sign(x)	-0.0004	0.001	0.0009	0.0008	18.2
l3. sign(x)	-0.0002	0.001	0.0008	0.0007	6.1
l4. sign(x)	3.89E-05	0.0007	0.0008	0.0007	3.0
l5. sign(x)	0.0001	0.0013	0.0008	0.0007	9.1
l. sqrt(x)	2.88E-06	0.0001	3.82E-05	4.24E-05	24.2
l2. sqrt(x)	7.86E-06	5.76E-05	4.11E-05	4.75E-05	24.2
l3. sqrt(x)	4.30E-06	2.77E-05	4.02E-05	4.80E-05	6.1
l4. sqrt(x)	-7.90E-06	3.91E-05	4.13E-05	4.95E-05	3.0
l5. sqrt(x)	-6.20E-06	7.74E-05	4.09E-05	4.87E-05	3.0
l.x	1.77E-07	1.44E-06	3.97E-07	6.28E-07	12.1
l2.x	-3.90E-08	7.75E-07	4.56E-07	7.57E-07	12.1
l3.x	3.90E-08	2.81E-07	4.55E-07	8.55E-07	3.0
l4.x	1.57E-07	5.14E-07	4.76E-07	8.76E-07	3.0
l5.x	4.64E-08	7.11E-07	4.69E-07	8.60E-07	0.0

Source: authors' calculations, using data from NASDAQ OMX Group (2012).

Panel C

This table presents average VAR output over 36 stocks. VAR was estimated for each stock and each year separately. The year is indicated in the first row of the table. Standard deviations of the averages are in the columns to the right of the averaged statistic. Only the first VAR equation is presented in which trade returns are the dependant variable. First column specifies the left hand side variables and their lags. Column "% of p-values < 0.05" gives the fraction of 36 coefficients that were statistically significantly different from zero at 5% level.
r – intraday stock returns between subsequent trades
sign(x) – trade sign that takes value of 1 if trade is buyer initiated, -1 if the trade is seller initiated and 0 if the trade was unclassified.
x – trade volume, signed positive if the trade was identified as buyer-initiated and negative if identified as seller-initiated. Unclassified trades have a value of zero.
sqrt(x) – square root of trade volume signed analogically to *x*.

Year			**2009**		
	Avg. R-squared = 9.9%			Avg # of obs.(Std. Dev.) = 4469 (4211)	
Independent variable	Avg. coeff.	(Std. Dev.)	Avg. SE	(Std. Dev.)	% of p-values < 0.05
l.r	-0.3078	0.0891	0.0227	0.01	100.0
l2.r	-0.1181	0.0769	0.0235	0.0102	88.6
l3.r	-0.0495	0.0617	0.0231	0.0099	57.1
l4.r	-0.0323	0.043	0.0224	0.0095	31.4
l5.r	-0.0144	0.0319	0.0204	0.009	31.4
l.sign(x)	0.0002	0.0015	0.0007	0.0005	45.7
l2. sign(x)	-0.0005	0.001	0.0007	0.0005	31.4
l3. sign(x)	-0.0004	0.0009	0.0007	0.0005	14.3
l4. sign(x)	-0.0002	0.001	0.0007	0.0006	8.6
l5. sign(x)	-0.0003	0.0012	0.0007	0.0006	14.3
l. sqrt(x)	1.17E-05	6.26E-05	3.73E-05	3.64E-05	34.3
l2. sqrt(x)	1.75E-05	6.26E-05	3.75E-05	3.69E-05	25.7
l3. sqrt(x)	9.11E-06	4.73E-05	3.78E-05	3.78E-05	14.3
l4. sqrt(x)	8.97E-06	8.48E-05	3.95E-05	4.28E-05	8.6
l5. sqrt(x)	1.77E-05	7.74E-05	4.12E-05	4.37E-05	8.6
l.x	-4.44E-08	8.09E-07	4.65E-07	5.70E-07	11.4
l2.x	9.47E-08	8.14E-07	4.69E-07	5.74E-07	17.1
l3.x	1.71E-08	6.45E-07	4.78E-07	5.98E-07	5.7
l4.x	-8.53E-08	1.09E-06	5.23E-07	7.26E-07	8.6
l5.x	-1.42E-07	9.07E-07	5.56E-07	7.36E-07	11.4

Source: authors' calculations, using data from NASDAQ OMX Group (2012).

Panel D

This table presents average VAR output over 36 stocks. VAR was estimated for each stock and each year separately. The year is indicated in the first row of the table. Standard deviations of the averages are in the columns to the right of the averaged statistic. Only the first VAR equation is presented in which trade returns are the dependant variable. First column specifies the left hand side variables and their lags. Column "% of p-values < 0.05" gives the fraction of 36 coefficients that were statistically significantly different from zero at 5% level.
r – intraday stock returns between subsequent trades
sign(x) – trade sign that takes value of 1 if trade is buyer initiated, -1 if the trade is seller initiated and 0 if the trade was unclassified.
x – trade volume, signed positive if the trade was identified as buyer-initiated and negative if identified as seller-initiated. Unclassified trades have a value of zero.
sqrt(x) – square root of trade volume signed analogically to *x*.

Year			**2010**		
	Avg. R-squared = 9.6%		Avg # of obs.(Std. Dev.) = 4719 (3494)		
Independent variable	Avg. coeff.	(Std. Dev.)	Avg. SE	(Std. Dev.)	% of p-values < 0.05
l.r	-0.3011	0.0941	0.0204	0.0082	97.2
l2.r	-0.1283	0.0748	0.0211	0.0081	86.1
l3.r	-0.072	0.0445	0.021	0.0081	72.2
l4.r	-0.0429	0.0485	0.0204	0.0079	50.0
l5.r	-0.0308	0.0376	0.0185	0.0071	44.4
l.sign(x)	0.0001	0.0007	0.0004	0.0003	27.8
l2. sign(x)	-0.0001	0.0006	0.0004	0.0003	25.0
l3. sign(x)	-0.0001	0.0004	0.0004	0.0003	5.6
l4. sign(x)	-0.0001	0.0006	0.0004	0.0003	13.9
l5. sign(x)	-0.0001	0.0005	0.0004	0.0003	2.8
l. sqrt(x)	1.36E-06	2.10E-05	1.76E-05	1.27E-05	16.7
l2. sqrt(x)	4.48E-06	2.97E-05	1.76E-05	1.28E-05	19.4
l3. sqrt(x)	3.51E-06	1.77E-05	1.76E-05	1.28E-05	11.1
l4. sqrt(x)	4.57E-06	2.32E-05	1.82E-05	1.37E-05	11.1
l5. sqrt(x)	7.30E-06	3.06E-05	1.83E-05	1.36E-05	2.8
l.x	7.30E-08	2.23E-07	1.67E-07	1.29E-07	13.9
l2.x	3.56E-08	3.14E-07	1.65E-07	1.25E-07	8.3
l3.x	2.55E-08	1.93E-07	1.65E-07	1.24E-07	2.8
l4.x	-2.80E-08	2.08E-07	1.74E-07	1.35E-07	5.6
l5.x	-8.90E-08	3.87E-07	1.78E-07	1.37E-07	8.3

Source: authors' calculations, using data from NASDAQ OMX Group (2012).

Panel E

This table presents average VAR output over 36 stocks. VAR was estimated for each stock and each year separately. The year is indicated in the first row of the table. Standard deviations of the averages are in the columns to the right of the averaged statistic. Only the first VAR equation is presented in which trade returns are the dependant variable. First column specifies the left hand side variables and their lags. Column "% of p-values < 0.05" gives the fraction of 36 coefficients that were statistically significantly different from zero at 5% level.
r – intraday stock returns between subsequent trades
sign(x) – trade sign that takes value of 1 if trade is buyer initiated, -1 if the trade is seller initiated and 0 if the trade was unclassified.
x – trade volume, signed positive if the trade was identified as buyer-initiated and negative if identified as seller-initiated. Unclassified trades have a value of zero.
sqrt(x) – square root of trade volume signed analogically to *x*.

Year			**2011**		
	Avg. R-squared = 8.1%			Avg # of obs.(Std. Dev.) = 3995 (3465)	
Independent variable	Avg. coeff.	(Std. Dev.)	Avg. SE	(Std. Dev.)	% of p-values < 0.05
l.r	-0.2862	0.0544	0.0229	0.0098	100.0
l2.r	-0.1313	0.0537	0.0237	0.0103	94.1
l3.r	-0.0702	0.0381	0.0235	0.0102	76.5
l4.r	-0.0349	0.0387	0.0227	0.0096	61.8
l5.r	-0.0248	0.0365	0.0206	0.0085	38.2
l.sign(x)	0.0004	0.001	0.0005	0.0004	26.5
l2. sign(x)	-0.0002	0.0006	0.0005	0.0005	14.7
l3. sign(x)	-0.0002	0.0005	0.0005	0.0005	2.9
l4. sign(x)	3.88E-05	0.0005	0.0005	0.0004	5.9
l5. sign(x)	-6.24E-06	0.0006	0.0005	0.0004	17.6
l. sqrt(x)	1.63E-06	3.17E-05	2.50E-05	2.48E-05	2.9
l2. sqrt(x)	7.23E-06	3.03E-05	2.50E-05	2.50E-05	5.9
l3. sqrt(x)	5.48E-06	2.35E-05	2.54E-05	2.56E-05	0.0
l4. sqrt(x)	-6.49E-06	2.10E-05	2.47E-05	2.41E-05	0.0
l5. sqrt(x)	-4.18E-06	3.44E-05	2.45E-05	2.53E-05	5.9
l.x	-1.09E-08	2.88E-07	2.72E-07	3.01E-07	2.9
l2.x	-2.88E-08	4.10E-07	2.71E-07	3.02E-07	8.8
l3.x	1.64E-08	3.35E-07	2.78E-07	3.16E-07	0.0
l4.x	1.37E-07	3.17E-07	2.67E-07	3.01E-07	2.9
l5.x	5.60E-08	4.16E-07	2.65E-07	3.30E-07	2.9

Source: authors' calculations, using data from NASDAQ OMX Group (2012).

Table 8: Market quality estimation results from 6 VAR test specifications

Table summarizing the mean estimates of the lower bound of the standard deviations of the pricing error. Standard deviations of the mean of the estimates are in the parentheses. The means and standard deviations are multiplied by 100 to report results in % units. The estimates are obtained by computing Beveridge-Nelson decomposition of price series under 6 different specifications of vector auto-regression model. The specifications differ according to lag length and variable set: 3 and 5 lags were used without allowing contemporaneous effects between variables. Variable are as follows:
r – intraday stock returns between subsequent trades
x – trade volume, signed positive if the trade was identified as buyer-initiated and negative if identified as seller-initiated. Unclassified trades have a value of zero.
sqrt(x) – square root of trade volume signed analogically to *x*.
ln(x) – logarithmically compressed signed trade volume.

			Total sample	Subsamples on effective sample size			
				1 (best)	2	3	4 (worst)
		# of firms	92	11	27	27	27
		# of transactions	1724708	981188	139179	46230	8939
Dispersion of pricing error (Standard deviation) %	*3 lag VAR specifications*	*{r, x}*	0.573 (0.598)	0.177 (0.061)	0.355 (0.104)	0.636 (0.410)	1.551 (1.103)
		{r, ln(x)}	0.635 (0.649)	0.199 (0.077)	0.366 (0.104)	0.696 (0.453)	1.713 (1.003)
		{r, sqrt(x), x}	0.625 (0.663)	0.185 (0.066)	0.358 (0.104)	0.683 (0.457)	1.734 (1.097)
		# of transactions	1578490	939052	118455	35780	5878
Dispersion of pricing error (Standard deviation) %	*5 lag VAR specifications*	*{r, x}*	0.803 (1.296)	0.196 (0.068)	0.366 (0.101)	0.694 (0.391)	2.971 (2.753)
		{r, ln(x)}	0.794 (1.005)	0.213 (0.075)	0.390 (0.111)	0.847 (0.433)	2.295 (1.806)
		{r, sqrt(x), x}	0.888 (1.291)	0.208 (0.069)	0.385 (0.107)	0.824 (0.463)	3.124 (2.327)

Source: authors’ calculations, using data from NASDAQ OMX Group (2012).

Table 9: Institutional trading and trading experience effects on market quality

Table presents results of linear regressions with 2D clustered standard errors (clustered by stocks and days) which test how institutional trading and trading experience affects market quality. Dependent variable is absolute value of pricing error of every trade which is obtained from the first stage estimates. Independent variables measuring the impact of institutional trading include dummies for every combination: institution (active) – institution (passive), private trader (active) – institution (passive), institution (active) – private trader (passive); private trader (active) – private trader (passive) is not included in the regression as is used as a reference point. Experience is measured in 3 ways. Nr of trades - experience as cumulative number of trades that investor has made during his trading period in the Tallinn stock exchange. Traded volume – cumulative value of trades that investor has made during his trading period in the Tallinn stock exchange. Days of experience - cumulative number of trading days since the registration of the portfolio in the Tallinn stock exchange. Interaction variables between institution dummy and experience are included. Control variables are Wealth – average size of trader's portfolio recalculated on yearly basis, Average trade – average value of trader's transaction recalculated on yearly basis, Foreigner dummy – value of one if the trader is foreigner and zero if local, interaction terms with institution dummy, Opening dummy – equal to one if transaction occurred during the first half an hour of the trading day and Closing dummy – equal to one if transaction occurred during the last half an hour of the trading day. Control variables available only for individual traders: Male dummy – value one for male and zero for female, Age – days between birth year and trade date. Coefficients on stock dummies and monthly dummies are not reported. ln indicates that variable was transformed in a natural logarithm. (1) and (2) specifications include both institutional and private trades, (3) and (4) – only individual. The interpretation of the dummy variables should be as following: if the estimated coefficient on the dummy variable is b and the estimated variance of b is var(b) then the estimate of the percentage impact of the dummy variable on the dependent variable is calculated as

$$effect = 100 \times (e^{\left(b - \frac{var(b)}{2}\right)} - 1)$$

*,**,*** indicates that coefficient is significant at 10% , 5% or 1% level respectively. T-statistics are provided in brackets.

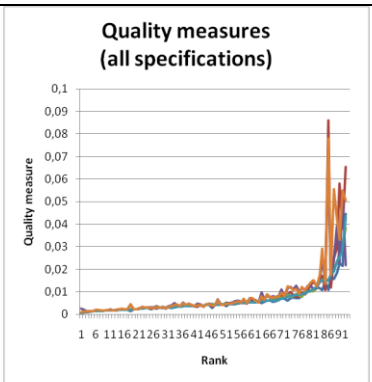
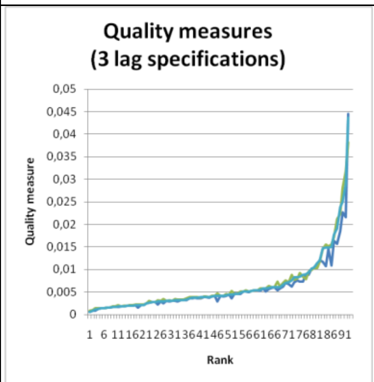
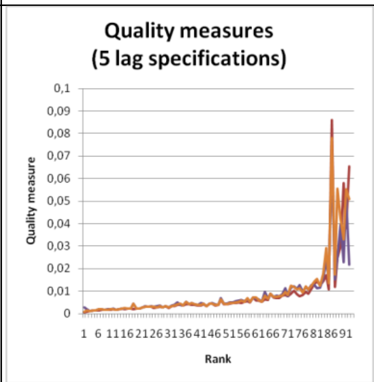
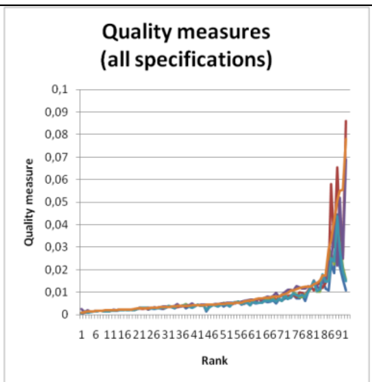
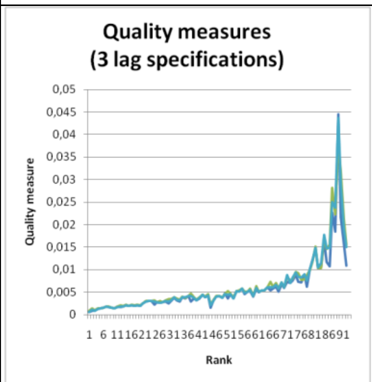
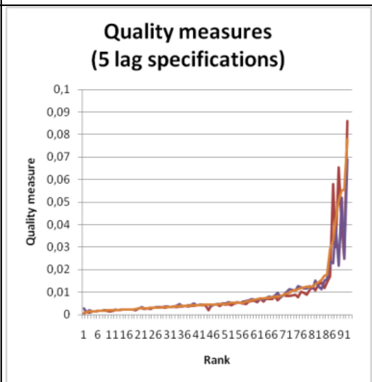
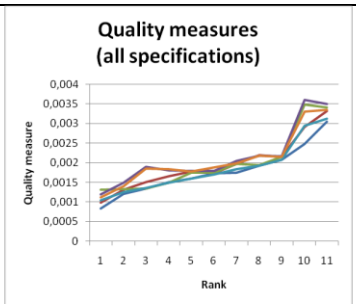
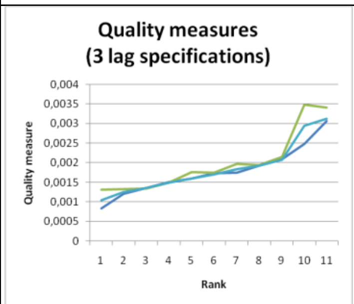
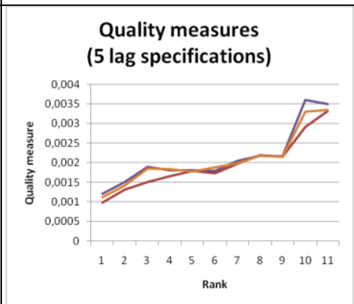
Dep. var: ln(absolute value of pricing error)	(1)	(2)	(3)	(4)
ln (Nr of trades)	-0.0093**		-0.0078*	
	(-2.62)		(-2.08)	
ln (Traded volume)		-0.0076**		-0.0075*
		(-2.23)		(-2.13)
ln (Days of experience)	0.0126**	0.0120**	0.0138**	0.0139**
	(2.76)	(2.56)	(2.83)	(2.79)
Institution*ln(Nr of trades)	-0.0057			
	(-1.12)			
Institution*ln(Traded volume)		-0.0075		
		(-1.58)		
Institution*ln(Days of experience)	-0.0041	-0.0008		
	(-0.57)	(-0.11)		
Institution (active) - Institution (passive)	-0.2394***	-0.2395***		
	(-14.98)	(-15.02)		
Private (active) - Institution (passive)	-0.2242***	-0.2247***	-0.2379***	-0.2392***
	(-15.05)	(-15.22)	(-15.32)	(-15.63)
Institution (active) - Private (passive)	-0.0716***	-0.0717***	-0.0699***	-0.0697***
	(-4.52)	(-4.54)	(-4.30)	(-4.28)
ln (Wealth)	0.0050	0.0074	0.0032	0.0061
	(0.91)	(1.30)	(0.57)	(1.04)
ln (Average trade)	-0.1025***	-0.0984***	-0.1048***	-0.1007***
	(-11.95)	(-10.85)	(-11.67)	(-10.46)
Foreigner dummy	-0.0297	-0.0297	-0.0324	-0.0318
	(-1.69)	(-1.69)	(-1.59)	(-1.55)
Institution*ln(Wealth)	-0.0039	-0.0052		
	(-0.54)	(-0.70)		
Institution*ln(Average trade)	0.0309***	0.0388***		
	(3.16)	(4.13)		
Institution*Foreigner dummy	0.0759**	0.0734**		
	(2.33)	(2.25)		
Male dummy			0.0088	0.0113
			(0.62)	(0.77)
ln (age)			0.0557**	0.0533**
			(2.97)	(2.83)
Opening dummy	0.0652**	0.0643**	0.1026***	0.1032***
	(2.84)	(2.79)	(4.04)	(4.06)
Closing dummy	0.0631***	0.0635***	0.0252	0.0251
	(3.49)	(3.51)	(1.17)	(1.15)
Constant	-6.1990***	-6.1940***	-6.6650***	-6.6381***
	(-55.72)	(-55.59)	(-36.59)	(-36.66)
No of observations	150,870	149,417	75,652	74,471
R-squared	0.1916	0.1907	0.1981	0.1968

Source: authors' calculations, using data from NASDAQ OMX Group (2012).

10. Appendix III: Figures

Figure 1: Quality measure results for 6 VAR test specifications

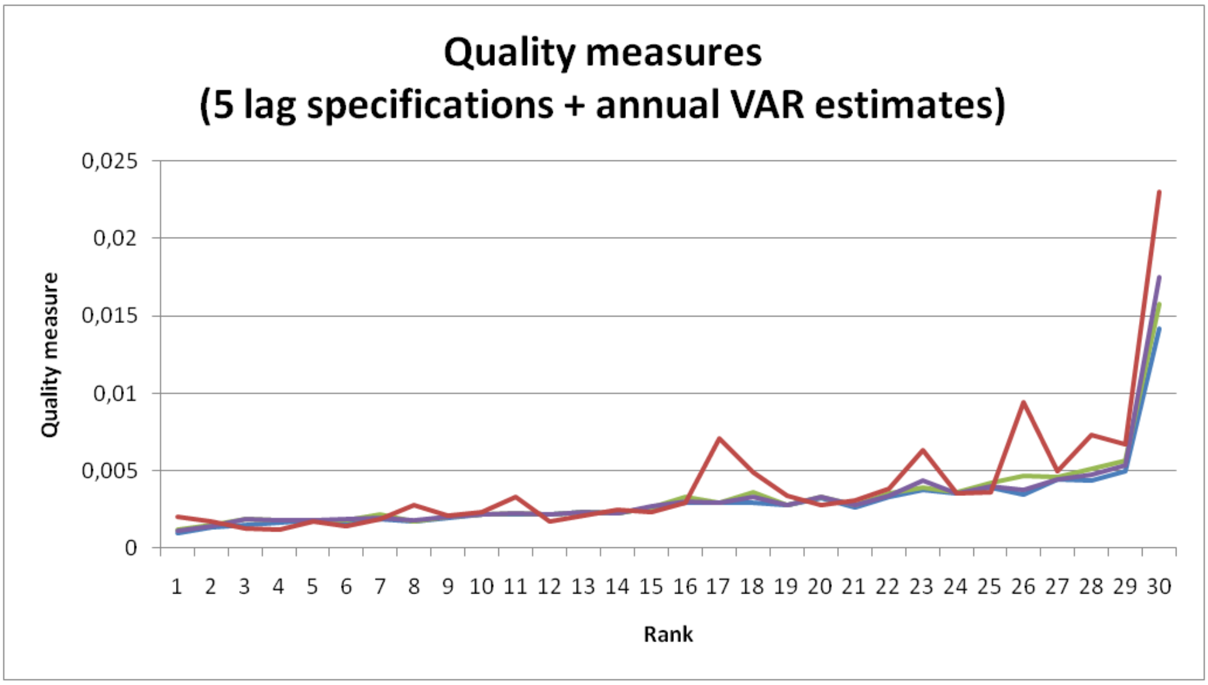
This matrix of graphs was composed to visualize the consistency of the standard deviation of the pricing error estimates obtained using VAR specifications with 3 different variable sets and two different lag lengths. Sorting stocks according to estimates obtained using *{r, sqrt(x), x}* 3 lag VAR specification seems to align lines in the upper middle graph, while sorting stocks according to estimates obtained using *{r, sqrt(x), x}* 5 lag VAR specification (middle row) does not seem to align the middle-right graph as well as upper middle graph. This is a loose indication that 3 lag VAR models produce more consistent estimates across stocks. Bottom row shows same results as the top row only for 11 stocks with the largest effective sample sizes.

	All 6 specifications	3 lag specifications	5 lag specifications
Sorted accordiong to *{r, sqrt(x), x}* 3 lag VAR specification. All 92 stocks.			
Sorted accordiong to *{r, sqrt(x), x}* 5 lag VAR specification. All 92 stocks.			
Sorted accordiong to *{r, sqrt(x), x}* 3 lag VAR specification. 11 stocks with the largest effective sample sizes.			

Source: authors' calculations, using data from NASDAQ OMX Group (2012).

Figure 2: Quality measure results of test versus final VAR specification

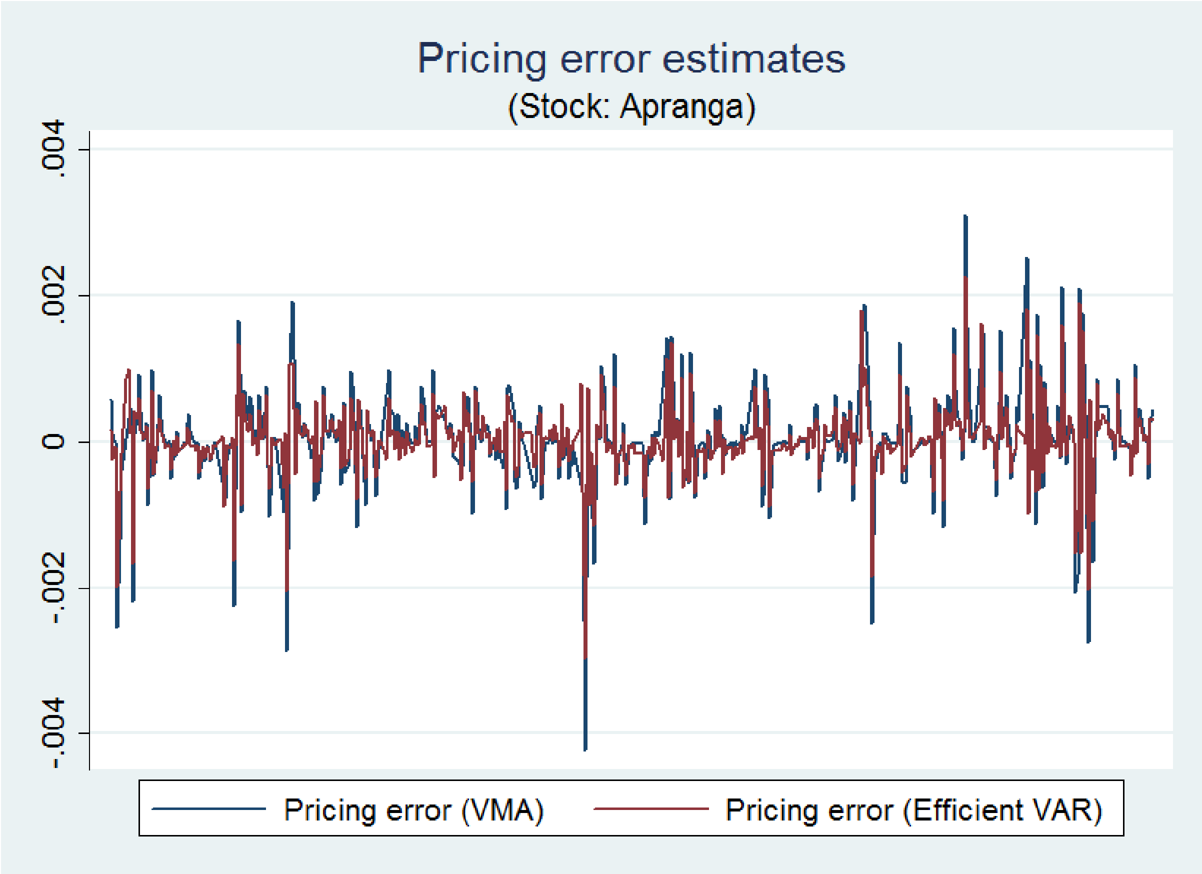
The figure is composed to visualize the difference in market quality estimates obtained using 3 VAR test specifications as opposed to the final VAR specification that is estimated for each year. The vertical axis denotes the estimate of the lower bound of the standard deviation of the pricing error. The horizontal axis denotes the rank of the stock according to the market quality estimates using *{r, sqrt(x), x}* 5 lag VAR specification. The highest differences between quality measures obtained using test and final specifications are present for stocks with most difference in VAR coefficients between years.



Source: authors' calculations, using data from NASDAQ OMX Group (2012).

Figure 3: Pricing error estimates under two alternative methods

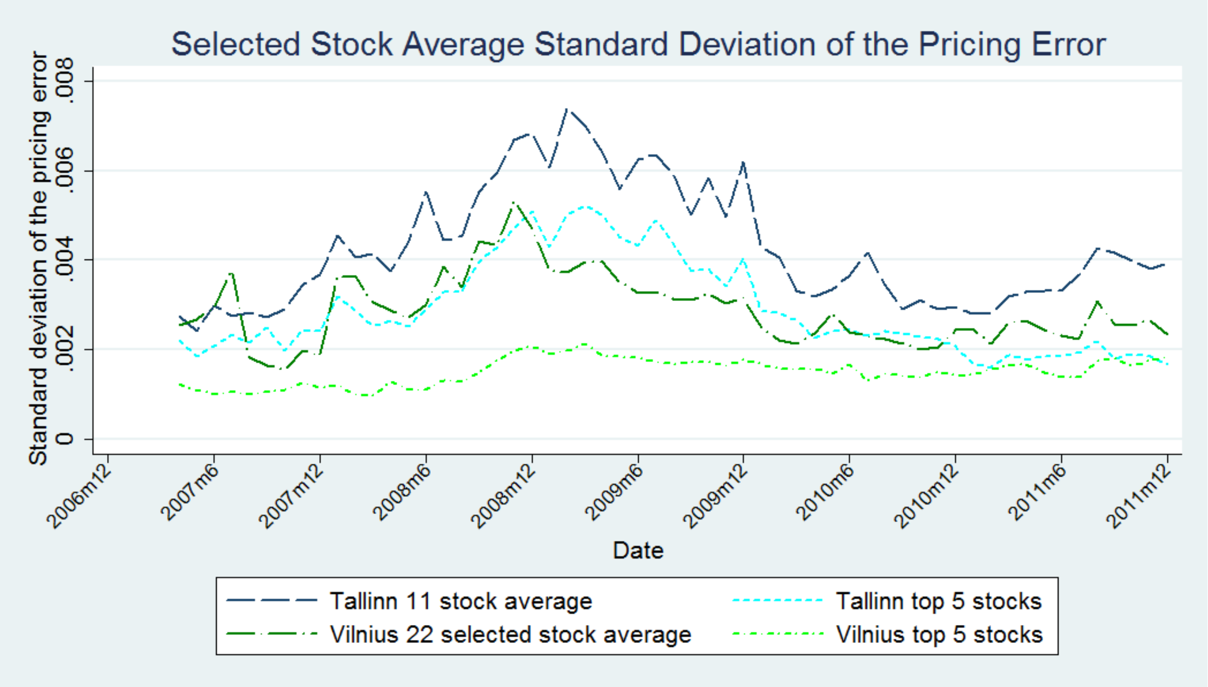
Figure illustrates the pricing error estimates using two different computation methods of Beveridge-Nelson decomposition. Estimates for 600 transactions of stock “Apranga” are graphed. Both computation methods used 2 lag VAR model with returns and signed square root of trade volume. The blue line shows the estimates calculated using VAR to VMA inversion method, while the red line is drawn from calculations obtained using more efficient method using formula suggested by Arino and Newbold (1998). From the graph one can observe that the results differ most at the extreme values. These differences between the two methods generally increase with use of more lags as well as more explanatory variables in VAR.



Source: authors’ calculations, using data from NASDAQ OMX Group (2012).

Figure 4: Average market quality of selected stocks

Figure illustrates the averaged estimates of the lower bounds of the standard deviations of the pricing errors for selected stocks in Vilnius and Tallinn stock exchanges in period 2007.04.01 – 2011.12.31. The estimates were computed at monthly frequency using Beveridge-Nelson decomposition. The units are in fraction of stock prices, meaning that standard deviation of pricing error of 0.002 is equivalent to 0.2% of stock price. The sample includes 22 stocks from Vilnius and 11 stocks from Tallinn stock exchange. The 11 stocks from Tallinn were used in second stage analysis. In addition to the selected stock averages, averages of 5 stocks with the lowest standard deviations of the pricing error in the respective markets were graphed.



Source: authors' calculations, using data from NASDAQ OMX Group (2012).

11. Appendix IV: Alternative computation method

Originally Hasbrouck used the following computation method to estimate the variance of pricing error. VAR regressions are easier to run in practice, but for further computation, VAR is transformed into vector moving average (VMA) representation:

$$\begin{aligned} r_t &= \hat{a}_0 v_{1,t} + \hat{a}_1 v_{1,t-1} + \hat{a}_2 v_{1,t-2} + \cdots + \hat{b}_0 v_{2,t} + \hat{b}_1 v_{2,t-1} + \hat{b}_2 v_{2,t-2} + \cdots, \\ x_t &= \hat{c}_0 v_{1,t} + \hat{c}_1 v_{1,t-1} + \hat{c}_2 v_{1,t-2} + \cdots + \hat{d}_0 v_{2,t} + \hat{d}_1 v_{2,t-1} + \hat{d}_2 v_{2,t-2} + \cdots, \end{aligned} \quad (1)$$

where notations ($\hat{}$) indicate estimates of parameters in question. Also $\begin{bmatrix} \hat{a}_0 & \hat{b}_0 \\ \hat{c}_0 & \hat{d}_0 \end{bmatrix} = I$ is an identity matrix.

$$s_t = \alpha_0 v_{1,t} + \alpha_1 v_{1,t-1} + \cdots + \beta_0 v_{2,t} + \beta_1 v_{2,t-1} + \cdots + \eta_t + \gamma_1 \eta_{t-1} + \cdots. \quad (2)$$

Where η_t are uncorrelated with all v_t components, however because of Beveridge-Nelson restriction (permanent and transitory components share same innovation) these terms drop out ($\eta_t = \gamma_1 = \cdots = 0$).

Variance of the efficient price innovations can be calculated as:

$$\sigma_\omega^2 = \left[\sum \hat{a}_i \quad \sum \hat{b}_i\right] Cov(v) \begin{bmatrix} \sum \hat{a}_i \\ \sum \hat{b}_i \end{bmatrix}. \quad (3)$$

And the variance of pricing error (measure of market quality) is calculated as follows:

$$\sigma_s^2 = \sum_{j=0}^{\infty} [\alpha_j \quad \beta_j] Cov(v) \begin{bmatrix} \alpha_j \\ \beta_j' \end{bmatrix}. \quad (4)$$

where $\alpha_j = -\sum_{k=j+1}^{\infty} \hat{a}_k$, $\beta_j = -\sum_{k=j+1}^{\infty} \hat{b}_k$.